SIMULATION MODELING AND ANALYSIS OF TNMCS FOR THE B-1 STRATEGIC BOMBER

THESIS

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Abstract

Simulation provides a method of modeling complex systems which would otherwise be impractical for quantitative experimentation. While other analytic techniques have been used to explore Total Non-Mission Capable [due to] Supply (TNMCS) rates, simulation offers a novel approach to discovering what aspects of the supply chain impact this metric.

This research develops a discrete event simulation to investigate factors which affect TNMCS rates for the B-1B by modeling the core processes within the Air Force (AF) supply chain. A notional fleet of 16 aircraft at a single air base (Ellsworth AFB, SD) is modeled based on historical supply and maintenance data. To identify and quantify the effects of various factors, an experimental design is used for analyzing the output of our high-level discrete event simulation. Additionally, two different approaches to reporting and modeling Air Logistics Center (ALC) stockage effectiveness (SE) are compared to our baseline simulation. This exploration shows several factors which significantly impact TNMCS rates and have the potential to reduce them to their current targets.

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To my wife, without whose love and support this thesis would still be an empty document.
Also, for my mother, whose hard work and dedication to education kept my drive over these past years.
And finally, to Poppa, I know this accomplishment would have made you so proud. You are missed every day.

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Finally, a debt of appreciation goes to my DARC family who was supremely supportive and flexible throughout this journey. Your professionalism during this time is greatly appreciated, and I'm looking forward to the fall.

Carl R. Parson

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SIMULATION MODELING AND ANALYSIS OF TNMCS FOR THE B-1 STRATEGIC BOMBER

1. Introduction

1.1 Background

In April of 2008, the Air Force Global Logistics Support Center (AFGLSC) was stood up with the responsibility of enterprise-wide planning of the Air Force (AF) supply chain and faces many unique challenges. Similar to supply chains found in various industries, the AF supply chain is considered a multi-echelon supply chain with many hubs fulfilling various demands. In addition to maintaining its own supply chain for reparable parts, the AF also interfaces with the Department of Defense (DoD) and government contractors to meet certain requirements. According to an Air Force Materiel Command (AFMC) source (Towell, Jan 2010) as of 30 Sep 09 the AF alone was responsible for managing 113,897 recoverable and consumable items enterprise wide. In order to manage this complex system, several performance and process metrics have been defined by AFMC. All of these metrics drive, and are driven by, the fact that the AF must have mission ready weapon systems, which is ultimately measured by aircraft availability (AA). Figure 1 shows the AA metric cycle as defined by AFMC.

Figure 1. Aircraft Availability Metrics Cycle

Critical to an individual weapon system's availability is its mission capable (MC) rate which is primarily a function of two other performance metrics: Total Non-Mission Capable [due to] Supply (TNMCS) and Total Non-Mission Capable [due to] Maintenance (TNMCM). Intuitively, if an aircraft is waiting on a part to arrive or for maintenance actions to occur, the aircraft is unavailable to accomplish its mission(s). TNMCS is, seemingly, a function of many factors that cause delays within the supply chain. However, previous studies (Fryman et al, Aug 2008; Fryman et al, Oct 2008) performed within the AF analytic community have not uncovered how specific factors affect TNMCS rates. MC is directly related to AA and provides more insight into the day to day processes that produce aircraft ready to perform their peacetime and wartime missions. We use MC in further discussion when referring to the health or operational readiness of a weapon system.

1.2 Problem Statement

In order to reduce TNMCS rates for a specific weapon system, it is important to understand how key factors in the Air Force supply chain impact the process. This thesis research uses historical data within an Arena ® simulation to model B-1 operations at a single air base and the supply chain process which results in TNMCS hours being accrued. Results from the simulation model are analyzed using an experimental design to measure the impact of specific factors on TNMCS.

1.3 Scope

The Air Force maintains, arguably, one of the most complex supply chains in the world; a portion of which supports aircraft maintenance, and thus MC. Specifically, ensuring on-time and cost effective stocking and delivery of parts in order to minimize customer wait time (CWT) is critical for achieving target aircraft MC rates. Influenced by various stochastic elements and external factors, the AF supply chain that supports aircraft maintenance for a single fleet of aircraft at an individual air base, as in our problem, is itself a complex system. Whether investigating the stocking policies at individual points in the supply chain, or simply the aggregated logistics response time, every node in the network is critical to providing a lean and agile supply chain. While much of the system is understood and strictly monitored at an individual level, little is understood about the behavior of the broad process. Thus, a simulated abstraction of the system is warranted so that estimates of the desired true characteristics may be discovered (Law, 2007). Simulation is an ideal method for studying complex systems, as well as exploring how changes to the inputs affect the responses (Banks, 2005).

1.4 Supply Chain Management

Supply chain management (SCM) is a broad term used to describe the management of the movement and storage of materials, inventory and finished goods from supplier to consumer, and is used in most industries. The Council of Supply Chain Management Professionals (CSCMP) defines SCM as “the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities” (CSCMP Glossary, 2010). The backbone of SCM is the ability to provide on demand customer service through parts fulfillment, product delivery, etc. As customer requirements are received, the order is expected to be fulfilled as quickly as possible. Though the customers of the AF supply chain may have unique requirements, they still function under this same principle. Within the realm of aircraft maintenance, the customer is the weapon system maintainer who is serviced by the AF supply chain, starting with the benchstock.

In many ways, management of the AF supply chain mirrors that of a commercial airline. Typically, commercial airlines focus on ensuring their aircraft meet the demand of their passengers, while controlling overall operating costs. Additionally, the competitive nature of the commercial airline industry drives a more cost efficient supply chain. Commercial airlines typically measure success by maintaining clean, modern aircraft, as well as maintaining positive safety records (Ayers, 1999). One benefit realized by the commercial airlines is that many of them maintain similar aircraft (such as the Boeing 747), and can thus integrate their supply chains using cooperative agreements. This not only appears to decrease overall operating costs, but reduces the complexity of the airline industry supply chain. In contrast, most aircraft maintained by the USAF are housed in a few select airbases, which contributes to the complexity of the supply chain.

The vast amount of resources consumed within the DoD provides an ideal environment for improvement through supply chain management. When considering the Air Force supply chain, even for a single weapon system at a single air base, a detailed model could have tens of thousands of inputs including characteristics for each part, operating details at and between various supply nodes, etc. Management of the AF supply chain is evaluated through a variety of performance metrics, the principle of which is MC.

1.5 Background on AF MC Analysis

The Air Force focuses on distinctive metrics driven by overall MC so that the weapon system's primary (and in many cases secondary) missions can be accomplished. It is also important to understand that MC is both the key input to the requirements process, as well as the best output measure of support to the warfighter (Maintenance

Metrics, 2001). MC rates are used to determine the Air Force's overall operational readiness. Pendley et al (2008) define MC rates as the percentage of possessed hours an aircraft is fully or partially mission capable (FMC/PMC respectively), or:

$$MC(\%) = \frac{FMCHours + PMCHours}{PossessedHours} * 100\% \qquad (1.1)$$

As previously discussed, one key performance metric of the AFGLSC is Total Non-Mission Capable [due to] Supply (TNMCS). TNMCS is a major driver of MC rates for the Air Force. Pendley et al (2007) also provide a means for calculating TNMCS:

$$\text{TNMCS } (\%) = \frac{NMCSHours + NMCBHours}{PossessedHours} * 100\% \qquad (1.2)$$

Where NMCS Hrs are the total number of hours a weapon system is Non-Mission Capable due to Supply (NMCS), and NMCB hrs are the total number of hours a weapon system is both NMCS and Non-Mission Capable due to Maintenance (NMCM).
From July 2008 to June 2009, the monthly TNMCS rates for the B-1 strategic bomber weapon system averaged 13.7%, more than one and a half times the target rate of 8%. Coupled with a standard deviation of 3.3%, these rates are cause for great concern for B-1 MC. While much has been published on AF MC rates and Total Non-Mission Capable [due to] Maintenance (TNMCM), there is little published work analyzing the TNMCS performance metric. As previously discussed, the complexity of the AF supply chain justifies the use of simulation to gain further insight into increasing a weapon system's MC.

1.6 Simulation of Supply Chains

Due to the wide variety of supply chains and their extreme impact on a business' efficiency, simulation is a frequently used analytic method. An article by Minghui Yang (2008) of Boeing brings to reality the difficulty that the airline industry, and similarly the Air Force, faces with maintaining a sufficient inventory for service requirements while minimizing the costs. The challenge he finds with using discrete event simulation to model an inventory system is that the vast number of parts required to service the airline industry significantly slows down run time, and grouping the parts into categories is extremely assumptive. Yang (2008) continues suggesting that it may be better to divide the parts into numerous categories, which is directly applicable to modeling the thousands of parts it takes to maintain a B-1.

Cheng (2008) discusses the modeling and simulation of a multi-tier supply chain with various suppliers as fulfillment centers. While this simulation models production facilities, there is still relevance to modeling the AF supply chain. While maintenance crews require part fulfillment for weapon systems, several tiers within the AF and DoD supply chains are used to provide service. Song, Li and Garcia (2008) discuss the simulation of a multi-echelon supply chain that determines optimal base stock inventory level within a distribution network similar to the AF spares supply chain. Their simulation showed promising results when using experimental design to develop a metamodel that accurately represents their system. While the goal of decreasing average total cost contrasts with the AF goal of increased MC, their research lends support to how simulation provides additional supply chain insight that pure data cannot explain. Further evidence of the ability of supply chain simulation to address various questions not easily answered through the real world system is is found in an article by Rossetti, Varghese, Miman, and Pohl (2008). Similar to investigating how various factors in the AF supply chain affect TNMCS, simulation helps them understand how the change in various forecasting techniques and policy updates will affect the system. While the simulation can increase general understanding of the system, the use of an experimental design will help explain how selected factors influence the system's responses.

1.7 Design and Analysis of Simulated Experiments

While developing a sophisticated model helps gain insight as to how a real world system works, implementing an experimental design with a validated model can help explain which factors in the model are driving the outputs. A benefit of using design of experiments (DOE) alongside a simulation is that the analyst can obtain critical information about the real world system with even a simple 2^k full factorial design using a wide selection of easily controllable simulation parameters as factors set at high and low levels. Sanchez (2007) writes that while there's a rule of thumb that magnitudes of interaction are reduced as the numbers of factors increase, one can expect to find stronger interactions using a simulation than within an actual experiment. A goal that is discussed by Sanchez is that of using DOE in simulation to find robust decisions or policies, where "the decision should not be based solely on mean performance and how close it is to a user-specified target value, but also on the performance variability" (2007). This is especially relevant when considering TNMCS rates. While reducing rates is important, being able to reduce the variability is equally significant. Sanchez continues by saying that one way to accomplish this is to reflect the trade-off between a good mean response and a small variance. “Examining the results in terms that involve only the decision factors will yield insight into whether or not specific decision-factor combinations are robust to uncontrollable sources of variation” (Sanchez, 2007). For a system as large as the Air Force supply chain, even when considering a single weapon system, it is important to know how policies will hold up to the various uncontrollable factors within the system.

1.8 Methodology

This research models the B-1 spares supply chain which supports a fleet of aircraft at a single air base, focusing on the investigation of TNMCS rates as a function of CWT, depot stockage effectiveness (SE), and time between unscheduled aircraft failures. The focus is not on the supply requirements of scheduled or daily maintenance actions, but on Code 3 landings of the aircraft. “A Code 3 aircraft has major discrepancies in mission-essential equipment that may require repair or replacement prior to further mission tasking” (AFI 21-101). There is more inherent variation with unscheduled failures, so it seems natural to scope the research to investigate the impact these stochastic elements have on TNMCS. This research also complements work done on high velocity maintenance (HVM) for the B-1 (Park, 2010), which tracks TNMCS within a computer simulation.

Previous work (Fryman et al, Oct 2008) used multivariate stepwise regression to explore why TNMCS rates deviated from their targets. In another study, Fryman et al et al (Aug 2008) used regression to examine how variation for spares funding impacted TNMCS. Neither study was able to explain the variation found with TNMCS across all weapon systems. In an interview with former AFMC analyst Dr. Jeffery Weir (2009), he explained that simulation would be an ideal method as it allows the investigator to step back and gain further insight on how the system functions, which is the core of this research. Modeling an entire complex system, such as the Air Force supply chain, can take a substantial amount of time and resources (Law, 2007), therefore, a proper abstraction of the system needs to capture the fundamental nature of the process.

The supply chain which supports weapon system spares requirements is a complex system that supports the global reach vision of the USAF. Banks et al (2005) suggest that the abstraction of such a complex system for a simulation study should be sufficiently detailed such that valid conclusions can be made about the system. The general logic flow for a single aircraft through our modeled system is shown in Figure 2.

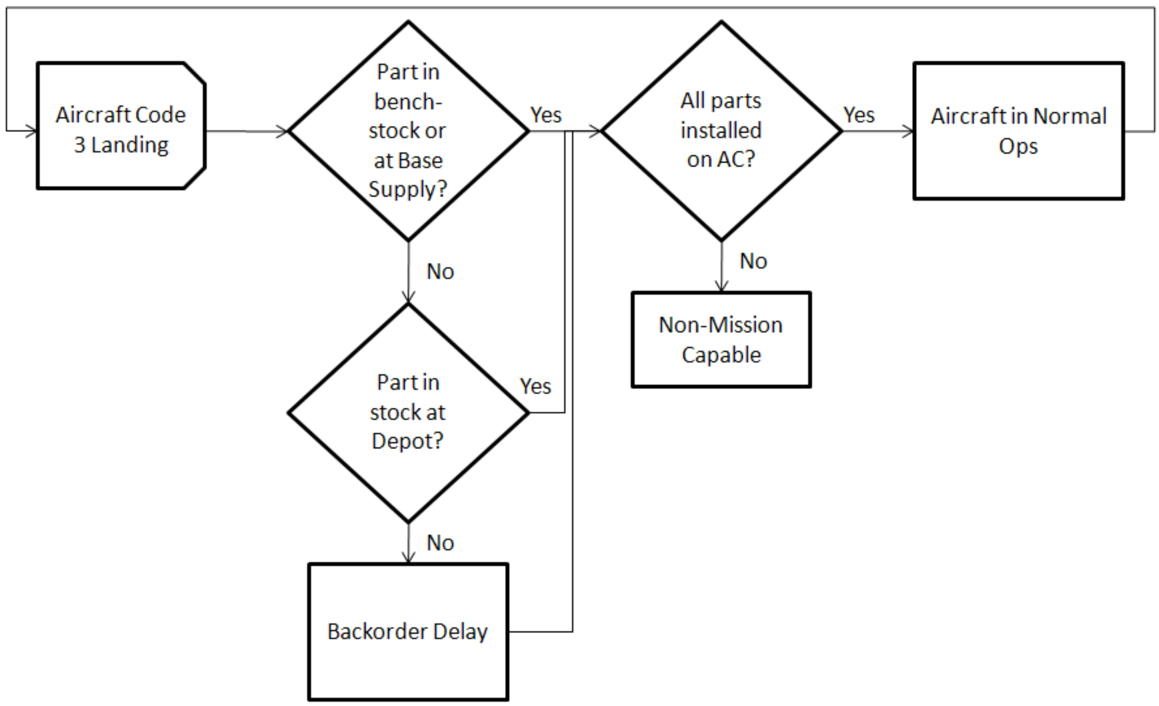


Figure 2. General Supply Flow

The aircraft are staggered through the system based on a time to next failure distribution developed by Park (2010), representing a Code 3 landing (unscheduled failure). Each failed aircraft has *n* number of parts that are split off and flow independently through the system until it is received at base supply and subsequently installed on the aircraft. Once base supply has all the parts requisitioned for that specific aircraft, they are batched, TNMCS hours are collected and the aircraft enters the normal operations delay.

Parts are separated into reparable and consumable as they have slightly different processes involved and collecting the statistics for each type is desirable. Base supply is checked to see if the part is immediately available, if not, the part is sourced from its representative depot.

For the purposes of this research, a part can only be sourced from three locations: DLA, ALC or a lateral source of supply. The Air Force negotiates the mean delivery time policies with the DLA. Thus, any part being sourced from DLA is simply done via a delay which models the time from order to receipt at base supply.

Since the Air Force influences its own depot level policies, the ALC source was given an additional level of fidelity within the model. One such policy is that of a maintainer laterally sourcing the part. Air Force policy (AFMAN 23-110) requires a maintainer to source a part at the depot level if the part is available. To this end, a decision is made whether or not the ALC has the part. If the part is not immediately available, a percentage of the parts are then able to be sourced laterally, with the rest going to a depot level backorder delay.

As stated before, parts being sourced laterally are only sourced if they are not available within the other tiers of the supply chain. Similar to the DLA, only the delay portion of the lateral source is modeled, as the delay in a part coming from another base will generally only be the shipping time, with a short delay for processing.

1.9 Outline

Chapter 2 provides details on the development of the model as well as some analytical results. Chapter 3 is an application of the model to a case study focused on a representative fleet of 16 aircraft at a single air base, along with numerical results. Chapter 4 concludes the thesis by discussing significant findings and providing recommendations for future research. Chapters 2 and 3 are structured as an individual journal paper and conference proceeding.

2. Simulation of Total Non-Mission Capable due to Supply (TNMCS) for the B-1 Bomber

2.1 Introduction

In the 1960's, the need for the development of a long-range, conventional multi-role bomber was identified, and the concept of the B-1 strategic bomber arose. In December of 1974, the first four B-1A embarked on their maiden flight. With a top flight speed of Mach 2.2, low altitude flight capability and the ability to deliver short-range nuclear attack weapons, the B-1A was not a cost effective option and was terminated in 1977. A less expensive and more capable version, the B-1B, eventually became a key part of President Reagan's Strategic Modernization Program with 100 aircraft slated for acquisition by 1988. During recent combat operations, the B-1B became known for its ability to fly few sorties, while dropping significant amounts of payload on target (Park, 2010). Thus, increasing availability for this highly capable aircraft is key to achieving air superiority.

2.2 Overview

Considerable amounts of time, money and manpower are invested in ensuring mission capability (MC) within the United States Air Force. The supply chain which supports aircraft maintenance is a critical component in maintaining mission readiness. As with many organizations, metrics have been established so that decision makers have a quick method of measuring the status of their respective systems which support successful mission execution. A key metric used by leadership to gauge the health of the spares supply chain is Total Non-Mission Capable due to Supply (TNMCS). TNMCS is more explicitly the amount of time aircraft are Not Mission Capable due to Supply

(NMCS) plus Not Mission Capable due to Both [supply and maintenance] (NMCB) (AFI 10-602, 2005).

TNMCS is also closely related to mission capable (MICAP) parts. A MICAP is simply a part that must be repaired or replaced before a weapon system is MC. By definition, a TNMCS aircraft can then be thought of as an aircraft with one or more MICAP parts. MICAP parts can, however, extend beyond our scope as they can also be reparable parts which accrue hours because they're awaiting maintenance actions. This research focuses on MICAP requirements through the supply chain (no explicit modeling of maintenance) and their relationship to TNMCS.

As TNMCS is a key measure of the health of the supply chain which directly impacts MC rates, understanding core components which affect these rates is critical. Previous studies were done to develop weapon system models to explain deviations from approved USAF TNMCS targets (Fryman et al, Oct 2008) and to determine the impact of spares funding on TNMCS (Fryman et al, Aug 2008). While these studies used sound analytical techniques, their results were unable to define any specific factors that explained the variability in TNMCS across all weapon systems.

This research develops a discrete event simulation model of the supply chain which supports spares activity for maintenance actions at a single air base for a single weapon system – the B-1 Bomber. Abstractions of three main processes are used in the simulation to gain an aggregated understanding of what factors significantly impact our responses of interest. The first process highlights normal operations within a standard maintenance shop at the air base. Next, the reparable and consumable processes look at decisions made when parts are required from other echelons of the supply chain. Finally, the source of supply process provides a general model of depot level supply processing.

Though much has been done which applies simulation to supply chain modeling, application of simulation to TNMCS is a novel approach. Simulation is often used to determine the impact of different policies on an organizations supply chain. Manuj et al (2007) explain that through simulation, effects of certain changes in a system can be observed which would otherwise be impossible to accomplish. Another goal of supply chain simulation can be system or parameter optimization (Kumar et al, 2007). Many such studies (Chan, 2005; Cheng, 2008) focus on responses such as transportation costs, inventory costs, utilization of resources, inventory level, lead times and order cycle times. The methodologies used in this research follow the approach of modeling a system such that numerical experiments can be done to provide a better understanding of how the system works under certain conditions (Kelton et al, 2007).

2.3 Model Development

Our research models 16 B-1 bombers at Ellsworth AFB, SD over a five year timeframe through the use of Arena simulation software. Sixteen bombers represents a typical number of aircraft stationed at Ellsworth AFB at any given time considering aircraft in Programmed Depot Maintenance (PDM), deployment, or other activities requiring an aircraft to be off station (Park, 2010). Each bomber begins a cycle through our model based on Code 3 landings, which represent unscheduled failures. We first look at the general flow of an aircraft through the system.

2.3.1 General Aircraft Cycle

The model is developed such that all aircraft enter the system simultaneously and cycle through the system over a five year period for each replication. An initialization period of 50 days is used to realistically space aircraft throughout the system before we begin collecting statistics. The cycle for each aircraft begins based on a time to next failure (TNF) distribution. An aircraft is considered in "normal operations" until its TNF, representing a Code 3 landing. In maintenance terms, a Code 3 aircraft "has major discrepancies in mission essential equipment that may require repair or replacement prior to further mission tasking" (AFI 21-101). Each Code 3 aircraft has an associated number of failed parts, assigned through the use of a discrete distribution. At the beginning of the cycle each aircraft is represented as a single entity. Upon a failure, each aircraft is then separated into its unique number of broken parts, with each part becoming a separate entity that runs independently through the rest of the system. A representation of the cycle is shown in Figure 3.

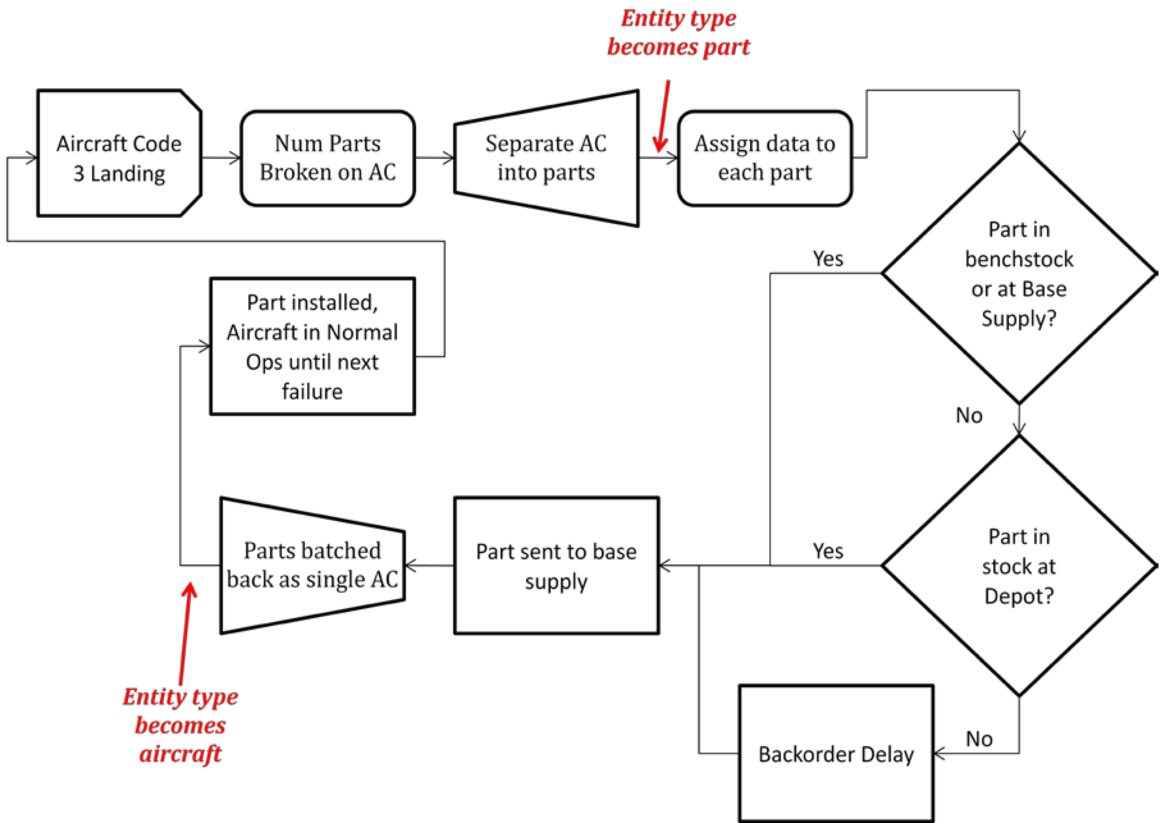


Figure 3. Generalized Cycle Flow

Each failed part is first assigned a Federal Stock Class (FSC) number, as well as several additional attributes required at latter points in the simulation. One such attribute is immediately used and decides whether a part is reparable or consumable. The reparable and consumable parts processes generally mirror one another except that certain consumable parts are able to be pulled from the maintainer's benchstock. The benchstock consists of a certain number of consumable parts frequently used to maintain an aircraft that are readily available, and already owned, by the maintenance personnel. Though managed by the DLA, these parts are authorized for stocking at the base level without additional reporting requirements. If not available through benchstock, base supply is then checked to see if a part is available to replace the broken one. If the part is available, it is put back on the aircraft which either waits on other repaired/replaced parts to arrive or re-enters normal operations. If the part is not available, it is then sourced from an Air Logistics Center (ALC) or the Defense Logistics Agency (DLA) and MICAP hours begin accruing for the individual part. One special circumstance of sourcing from the ALC is that if the part is not available the maintainer can attempt to source the part laterally. After a delay, calculated based on the source of supply, each part returns to base supply and MICAP times are recorded. All parts for a given aircraft wait in a batching queue until the last part arrives. Once the last MICAP part arrives the total number of MICAP hours for that part become the aircraft's TNMCS hours and are then recorded by aircraft. The aircraft then enters into normal operations until its next unscheduled failure occurs, and the cycle restarts. Screenshots of the full model in Arena are shown in Appendix A.

2.3.2 MICAP and TNMCS Hour collection

A key part of our logic was to properly capture MICAP and TNMCS hours. As part of our verification efforts in the initial phases of simulation development, we discovered significantly more hours than should be realized being recorded for each MICAP part and TNMCS aircraft. When MICAP or TNMCS hours (referred to as hours for the remainder of this section) were collected, if a mark time attribute for each part (TNMCS_Start) was not previously set, Arena would automatically assign a value of zero to that attribute, creating extremely large values for hours accrued. We tracked these large times to a small percentage of parts associated with a Code 3 landing that have no effect or only a partial effect on MC (we do not explicitly consider partially mission capable aircraft in our model) – these are not MICAP parts. By adding logic as shown in Figure 4, we flagged parts as either not MICAP (MC flag = 1; no hours accrued) or MICAP (MC flag = 2; mark time set to begin accrual of hours) to correctly determine when to start tracking applicable hours.

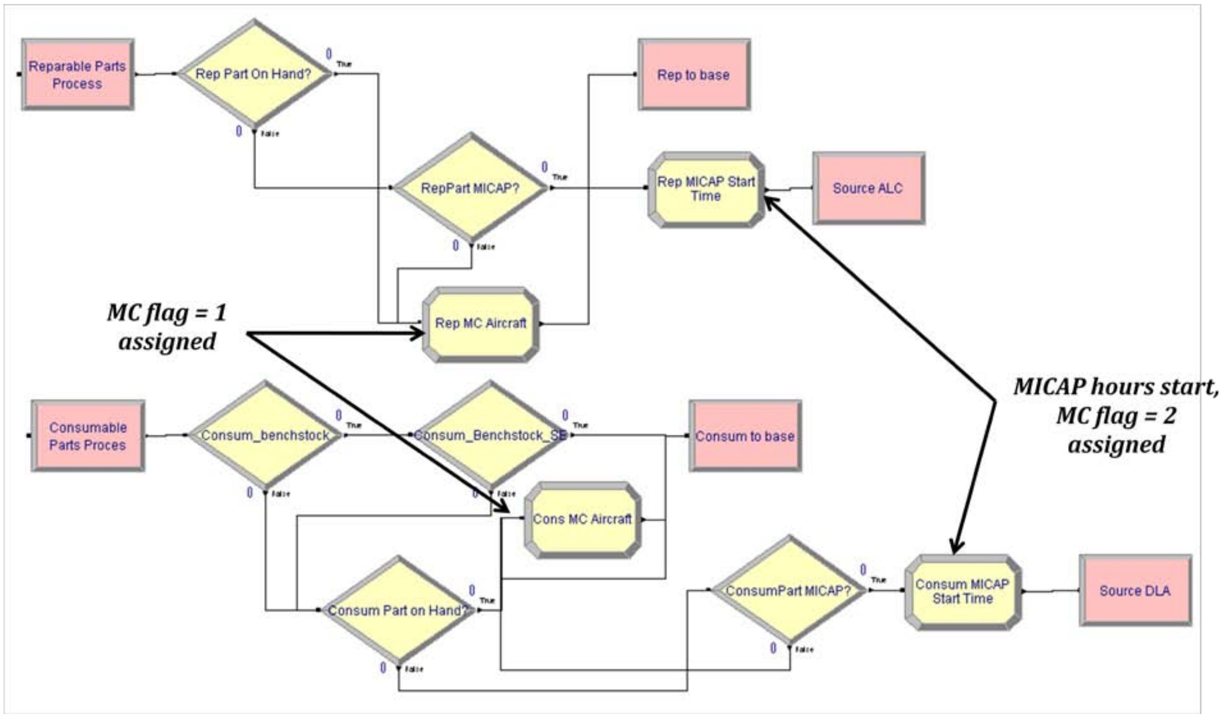


Figure 4. Reparable/Consumable Simulation Logic

The logic to determine when we stop accruing hours is shown in Figure 5. The initial decide node conditions on whether or not the part has MC flag = 2. If it does, then MICAP hours are recorded, if not then the part goes straight to the batching process, which waits for any more parts from the same aircraft. Once all the parts for an aircraft have arrived, they are batched into a single aircraft entity. This aircraft is assigned the attributes from the last arriving part, including the accrued MICAP hours as well as the MC flag previously discussed.

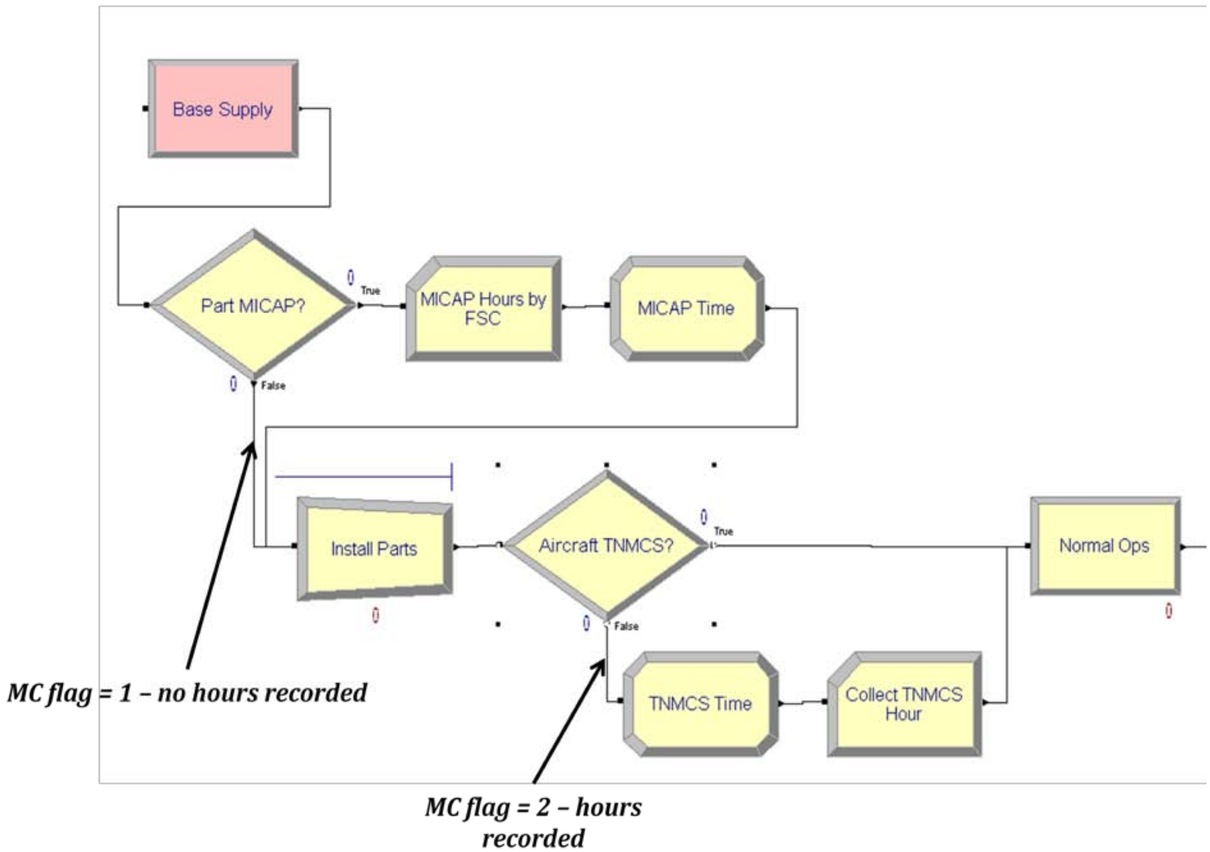


Figure 5. Process for Parts Received at Base Supply

Another decide node checks to see if the aircraft has MC flag = 1. If it does, then no hours accrue, otherwise, TNMCS hours are recorded and the aircraft enters into normal operations. This last decide node covers the rare case when our modeled Code 3 landing resulted in only non-MICAP parts failing, resulting in no MICAP or TNMCS hours being accrued.

<u>2.3.3 Assumptions</u>

Throughout model development, various assumptions had to be made such that the scope was maintained. Some key assumptions are:

- All reparable parts are sourced from ALC and all consumable parts are sourced from DLA
- An attempt must be made to source a reparable part from ALC before sourcing it laterally (i.e. if a part is at the depot level, it must be sourced from the depot)
- As these policies are negotiated independently, all parts sourced from DLA run purely through a delay, with no other depot level decision policies modeled
- No use of parts from already non-mission capable aircraft, or cannibalization (CANN), occurs within the model
- No maintenance was explicitly modeled, however NMCB is inherent when calculating MICAP hours and is therefore included in our TNMCS values
- If a part is not MICAP it is sent directly to base supply and no MICAP hours are accrued

2.4 Supporting Data

With the logic for our model defined, we turn to the underlying data that truly drives this simulation. Maintenance and supply data from a five year period (Jan 05-Dec 09) was gathered from the Logistics Installations and Mission Support – Enterprise View (LIMS-EV) as well as from maintenance and logistic subject matter experts (SMEs). From this data, empirical and theoretic distributions were developed to capture the stochastic elements of the model. Table 1 gives a breakdown of the data collected and its respective source, while Table 2 provides a summary of the various distributions fit within the model. The Arena input analyzer reports for these distributions can be found in Appendix B.

Table 1. Data Collection Source

Data Requirement	Source
Number of Broken Parts per failure	LIMS-EV, Ellsworth SME
MICAP hours	Ellsworth SME
FSC Data	LIMS-EV
Time to Next Failure (Code 3 landing)	LIMS-EV
ALC %	LIMS-EV
Base Supply Stockage Effectiveness (SE)	LIMS-EV
Benchstock SE	Ellsworth SME
SoS Processing Delays times	LIMS-EV

Table 2. Fit Distributions

Description	Expression
Number of Broken Parts	DISC(.53,1,.79,2,.89,3,.94,4,…,1,12)
ALC Backorder Delay	MX(1,ANINT(-.001 + LOGN(ALC_α,ALC_β))
DLA Processing Delay	MX(1,ANINT(-.001 + LOGN(DLA_α,DLA_β))
Lateral Processing Delay	MX(1,ANINT(-.001 + LOGN(Lat_α,Lat_β))
Time until Next Failure	MX(0,1.5*ANINT(-0.001+WEIB(TNF_ α,TNF_β)))
ANINT – Rounds the expression to the nearest integer DISC – Expression pulls values from a discrete distribution with given parameters LOGN – Expression pulls values from a Lognormal Distribution with given parameters MX – Maximum Value of all values in the expression WEIB – Expression pulls values from a Weibull Distribution with given parameters	

While the simulation focuses on a fleet of 16 aircraft, data from all B-1 requisitions was collected to create a better picture of the demands that are placed on the supply chain. For this study, data was aggregated, as recommended by Yang (2008), by categorizing parts by their Federal Stock Class (FSC) numbers. Thirty-two FSCs were selected to capture 80% of all supply requisitions as well as 83% of all MICAP hours in a five year period at Ellsworth. The remainder of the parts were rolled up into one consolidated FSC. The selected FSCs vary widely, from miscellaneous aircraft accessories, radar equipment, to other items under greater scrutiny such as engine components and accessories. Further descriptions of the FSCs are available in Appendix C. While no cost is modeled for this research, it is interesting to notice that several of the FSCs modeled appear to be inexpensive, consumable items. Specifically, five of these FSCs alone (5331, 5305, 5935, 5310 and 5306) represented almost 7% of the total MICAP hours over the past five years.

Several challenges arose when collecting the data from LIMS-EV. One significant challenge was that LIMS-EV data tracks every requisition through the supply chain, so no supply data is available which directly associates a supply requisition to a specific airframe or aircraft failure. Substantial portions of data were filtered and not used, as the majority of the requisitions are for typical day-to-day maintenance operations where no MICAP hours accrue. Another issue was that while the majority of the data was gathered from LIMS-EV, there was no single way to obtain all the data in one report, so multiple reports had to be run. This caused extensive disconnect when developing the distributions represented in Table 2. In most cases, five years of data was filtered through such that distributions were constructed that appear to be representative of the current system. The distributions were generally created using the input analyzer function of the ARENA simulation tool used to develop this simulation. In all cases, the data was filtered down manually to its respective set, collected into separate text files and the best fit was selected based on the outputs provided.

2.5 Verification and Validation

Crucial to any simulation study is verification of model construction and validation to ensure that the model is a sufficiently accurate representation of the system. Substantial verification (such as our previous discussion on capturing correct MICAP and TNMCS hours) and validation efforts went into the development of our model. An iterative review process occurred with an AFMC analyst before presenting it in an open forum to a panel of six more AFMC analysts. To ensure that the model characterized the true nature of the system as scoped for this research, several comments and suggestions made were implemented into the current model.

Validation for the outputs of our model were run against historic data, as well as through SMEs within the AF logistical analysis community. As the primary response for the simulation, TNMCS rates were done at the aircraft level, as well as aggregated over all aircraft. The responses obtained showed a range that was wide enough to encompass the variation found in the system, while being sufficiently accurate. Two primary metrics used for validation are shown in Table 3.

Table 3. Validation metrics

	Historical data	Simulated Data*
Avg TNMCS Rate	11.46%	(9.36%, 15.61%)
Avg MICAP Time by part	164 hours	(129 hours,193 hours)

* range over 20 reps

2.6 Experimental Design and Methodology

The key focus for the analysis of this simulation was the effects of differing levels of supply chain support, as well as time between Code 3 failures. As outputs, two primary responses were gathered to gauge the factors impact. These responses are:

- TNMCS Rates (by aircraft, and overall)
- MICAP Hours (total and by FSC)

These responses are of great interest to the Air Force Global Logistics Support Center (AFGLSC) as little is currently understood about what factors affect them. A number of unique factors were selected to perform our analysis. These factors are:

- ALC SE rate
- Base supply stockage effectiveness (SE) Rate
- Percent of time part sourced laterally
- ALC backorder delay
- DLA processing time
- Lateral processing time
- Time until next failure (TNF)

These factors were selected because previous studies haven't investigated their affect on TNMCS. For each of the final four factors, a scaling factor was used for each expression such that high and low levels (± 10%) were used as design points. All of the variables used are set at the base rate as a midpoint, with high and low values being used for the experimental design. These specific values are seen in Table 4.

Table 4. Actual values for design levels

Factor	Low level (-1)	Base level (0)	High level (+1)
ALC SE Rate	80%	85%	90%
Base Supply SE Rate	88%	90%	92%
Lateral %	4%	5%	6%
ALC B.O. Delay	0.9*Expression	1.0* Expression	1.1*Expression
DLA Processing	0.9*Expression	1.0* Expression	1.1*Expression
Lateral Processing	0.9*Expression	1.0* Expression	1.1*Expression
TNF	1.35*Expression	1.5* Expression	1.65*Expression

2.7 Results and Anlaysis

The base model is run over five years of simulated time with a 50 day initialization period to ensure the aircraft are at various stages within the system before collection of statistics. Twenty replications are done such that sufficiently accurate estimates of the responses are captured. The results from the base case appear to adequately represent current B-1 TNMCS rates. The simulation provided a mean TNMCS rate for the five year period of 12.488%, with approximately 91k MICAP hours being accrued. While only two responses were used for the experimental design, several additional measures of performance (MoP) were collected from the baseline model. One such MoP is the TNMCS rate for individual aircraft. While showing a wide range over the twenty replications, these results represent the wide variability of TNMCS. A few samples of individual aircraft TNMCS rates are summarized in Table 5.

Table 5. Average TNMCS rate by aircraft (over 20 replications)

	Min	Mean	Max
AC 9	4.26%	10.19%	24.29%
AC 6	4.81%	12.52%	26.59%
AC 5	6.82%	14.18%	24.55%

Another MoP collected was the average number of MICAP hours per month by FSC. Again, results showed significant variation, but generally contained the historical average within the range over twenty replications as seen in Table 6.

Table 6. Monthly MICAP hours by FSC (over 20 replications)

FSC	Historic Avg	Simulated Min	Simulated Mean	Simulated Max
5865 – Electric Countermeasures	1052 hrs	425 hrs	868 hrs	2388 hrs
1560 – Airframe Structural Components	938 hrs	271 hrs	757 hrs	1445 hrs
1660 – AC HVAC and pressurizing equip	287 hrs	56 hrs	189 hrs	497 hrs

Upon validation of the base model, an experimental design was run beginning with a screening test as an initial investigation for significant factors.

2.7.1 Screening Test

A 12-run Plackett-Burman design was used as a screening test for the main effects. This test was used because the aliasing for these designs allows the estimation of *k* main effects using *k*+1 runs. As a resolution III design only allows for testing of the main effects, no higher order interactions were investigated. The levels for the screening test are summarized in Table 4, and the design matrix is shown in Appendix D. Models for both responses were found to be statistically significant with R^2_{adj} values of 98.6 and

98.5 (for TNMCS and MICAP hours respectively). However, two of these initial factors (Lateral % and Lateral SF) were found insignificant, with p-values of .1674 and .6399 respectively, as shown in Table 7.

Table 7. Screening test significance summary

Factor	F stat	p-value
ALC SE	139	.003
ALC SF	27.3	.0064
Base SE	524.7	<.0001
DLA SF	19.2	.0119
Lateral SF	.255	.6399*
Lateral %	2.84	.1674*
TNF SF	82.7	.0008
*Insignificant factors		

2.7.2 Full Factorial Design

Upon removal of the two insignificant main effects, a 2^5 full factorial design with one midpoint was used to investigate the remaining main effects. The model proved significant as shown in Table 8. However, when testing our assumptions of error normality, independence and constant variance, residuals analysis showed substantial nonlinearity (see Figure 6).

Table 8. TNMCS response ANOVA table

Source	**DF**	**Sum Squares**	**Mean Square**	**F-stat**
Model	5	0.024713	0.004942	269.25
Error	27	0.000496	0.000018	**p-value**
Total	32	0.025208		<.0001

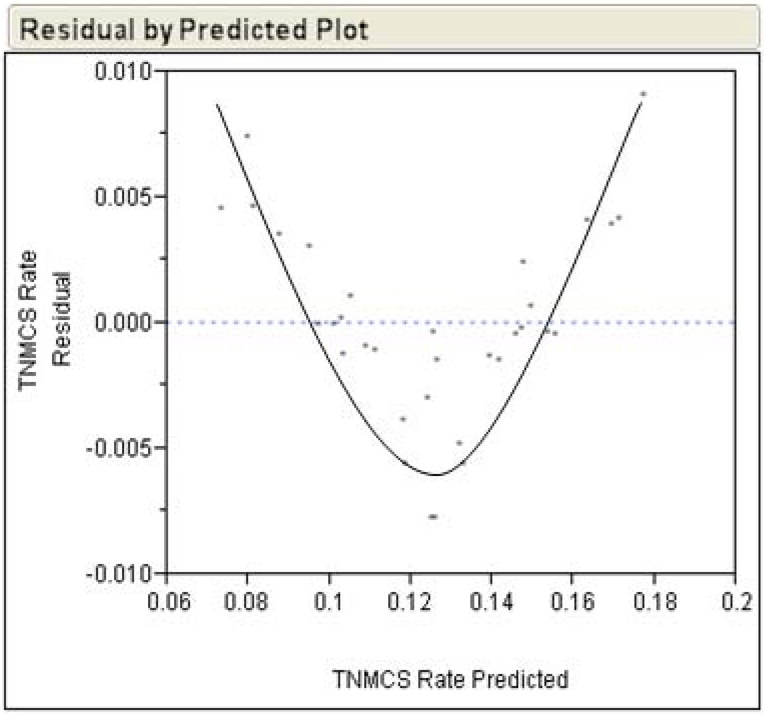


Figure 6. Experimental Design Residuals

Upon this discovery, all two factor interactions were introduced into the design, resulting in a better fit model, with our error assumptions maintained. For the full factorial model all main effects were found to be significant, which strengthens the results from our screening test. Additionally, five of the two factor interactions were accepted as significant (at the $\alpha = 0.05$ level). Several of the two way interactions provide some intuitive results. The first is the interaction between ALC SE and ALC SF. This type of interaction makes sense as the SE at a depot has an impact on how often they must backorder parts. Similarly, Base SE and ALC SE also show significance within their relationship. It seems natural that the two SE factors would have an interaction effect; if the part is not available at the base, then the depot is the next echelon for part requisition. Thus, if neither of these sources have the part, it will have an effect on

MICAP hours and TNMCS. Finally, TNF SF only had real significance when interacting with Base SE. This would say that as the TNF varied, the SE at the base level needs to be agile enough to handle the increased or reduced requirements. These results provide significant insight into factors and interactions that affect TNMCS. Figure 7 shows the ANOVA table with associated R^2 values and coefficient estimates for the final model.

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	0.02517175	0.002517	1522.091
Error	22	0.00003638	1.654e-6	**Prob > F**
C. Total	32	0.02520813		<.0001*

Summary of Fit

RSquare	0.998557
RSquare Adj	0.997901
Root Mean Square Error	0.001286
Mean of Response	0.125239
Observations (or Sum Wgts)	33

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.1252388	0.000224	559.45	<.0001*
ALC SE(80,90)	-0.011813	0.000227	-51.96	<.0001*
ALC SF(0.9,1.1)	0.0039375	0.000227	17.32	<.0001*
Base SE(88,92)	-0.022187	0.000227	-97.60	<.0001*
DLA SF(0.9,1.1)	0.0030625	0.000227	13.47	<.0001*
TNF SF(1.35,1.65)	-0.01075	0.000227	-47.29	<.0001*
ALC SE*ALC SF	-0.00075	0.000227	-3.30	0.0033*
ALC SE*Base SE	0.00275	0.000227	12.10	<.0001*
Base SE*DLA SF	-0.00075	0.000227	-3.30	0.0033*
ALC SF*TNF SF	-0.000562	0.000227	-2.47	0.0215*
Base SE*TNF SF	0.0023125	0.000227	10.17	<.0001*

Figure 7. Final Model JMP Reports

As stated, the error assumptions for this augmented design appear to be valid based on the residuals analysis. Figure 8 shows the updated residuals, plotted by observation. The wide dispersion and lack of any apparent autocorrelation lend evidence to the fact that the underlying assumptions hold for this model. Additionally, cube plots were investigated as a visual means for observing what levels of the factors are required to minimize

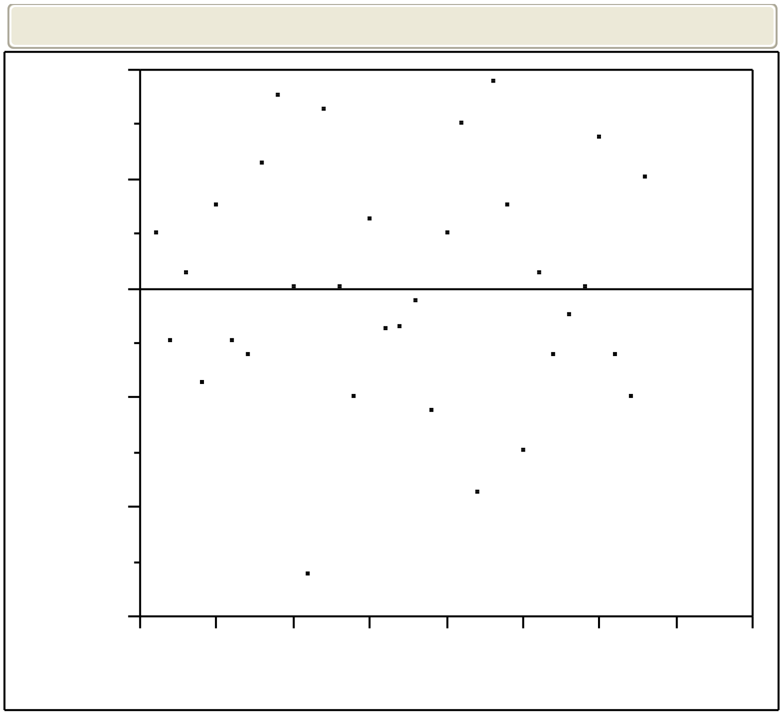


Figure 8. Residuals Plot by Observation

TNMCS. Intuitively, factors such as SE need to be increased, such that more parts are available as requirements come in. Similarly, the SF for the various delays within the system need to be reduced to subsequently reduce TNMCS. We also see a larger decrease in TNMCS from changes in SE than we see in reduced delays for our design. An example of these cube plots with optimal policies circled is shown in Figure 9.

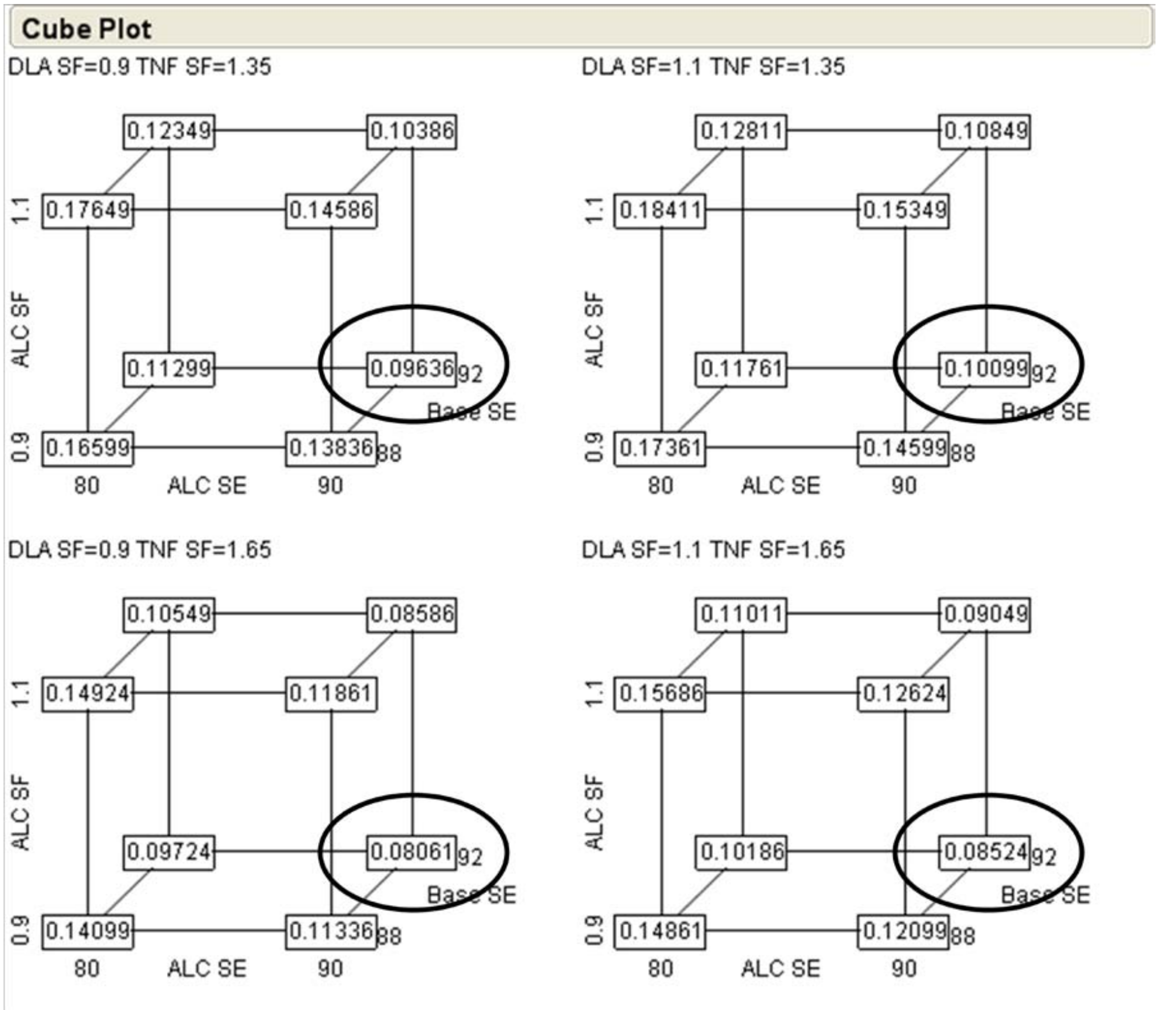


Figure 9. Cube Plots with TNMCS as the Response

One important result from this is that the AF target TNMCS rate for the B-1 weapon system (8%) is realized in at least one observation. The remaining observations show a significant decrease from the 12.5% rates from our baseline model.

When considering total MICAP hours as the response, almost identical results were found. All significant factors remained constant with very similar p-values across the board. Figure 10 provides a side by side view of the actual versus predicted values for the computed regression lines for both responses. The full analysis report for both TNMCS and MICAP as a response can be found in Appendix E.

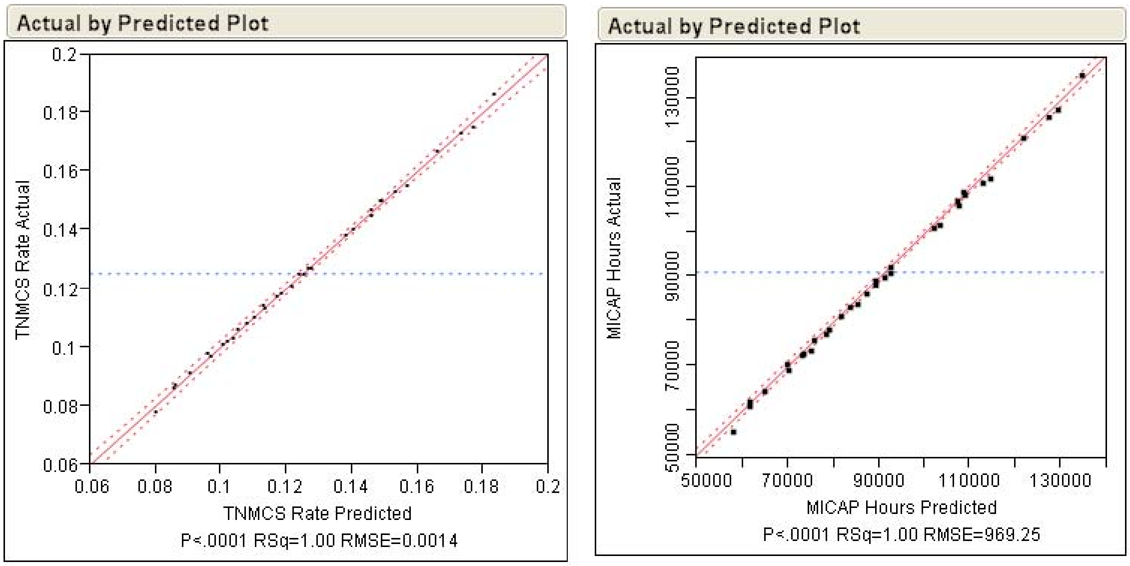


Figure 10. Actual by Predicted Plots for TNMCS (right) and MICAP Hours (left)

2.8 Conclusions

In order to begin understanding TNMCS rates, it is important to gauge where the variability is present within the system. These results provide an initial top-level view of the nature of TNMCS within the supply chain for a single weapon system at a single air base. Though this simulation provides a generalized abstraction investigating theoretic factors as well as current metrics, it presents a generalized view that may be beneficial from a management perspective. While these results might seem natural, they are an important first step into quantifying TNMCS so that resources may be made available that will help increase MC for a given weapon system.

In summary, there are factors present within the supply chain which affect both TNMCS rates, as well as MICAP hours. By understanding what these factors are, additional exploration can be focused on these areas, while expanding them to cover multiple aircraft at multiple air bases.

3. Case Study

Assessing Factors that Impact TNMCS for the B-1 Bomber

3.1 Introduction

As weapon systems within the United States Air Force (AF) become older, ensuring their mission capability (MC) through a lean and agile supply chain is critical. In April of 2008, the Air Force Global Logistics Center (AFGLSC) was stood up with the responsibility of enterprise-wide planning of the Air Force (AF) supply chain and faces many unique challenges. Total non-mission capable [due to] supply (TNMCS) is a metric used within the AFGLSC and a primary indicator of the health of the supply chain which supports weapon system spares requirements. TNMCS is also closely related to mission capable (MICAP) parts. A MICAP part is one which must be repaired or replaced before an aircraft is MC. For a broken aircraft, any required MICAP part accumulates hours while the aircraft is non-mission capable (NMC). When the last MICAP part for the aircraft is received, the total number of hours the aircraft was NMC is used to calculate its TNMCS hours.

For many aircraft, the observed TNMCS rates at a squadron or wing are substantially higher than the goals set by senior personnel within the AF. One such aircraft, and the focus of this study, is the B-1 strategic bomber. With a current rate close to 13%, 5% above its goal, there is cause for concern. Previous studies (Fryman et al, Aug 2008; Fryman et al, Oct 2008) were unsuccessful at finding specific factors which were able to explain or predict TNMCS across all aircraft. An important first step in being able to sufficiently define TNMCS rates for a weapon system is to understand the underlying factors or systems which affect the supply chain. This research develops a discrete-event simulation model that can help key personnel understand the process which defines TNMCS. Several significant factors are identified within the simulation. Further, this research investigates stockage effectiveness (SE) at the Air Logistics Centers (ALC) more thoroughly to understand its effect on TNMCS rates for a fleet of sixteen aircraft at a single airbase.

This paper begins with a brief background on MC analysis, followed by a concise discussion on the development of the simulation model. The simulation presented herein is an original contribution to the already minimal body of research on TNMCS. Initial results and analysis are provided as well as an in-depth investigation of ALC SE.

3.2 Background

The Air Force maintains, arguably, one of the most complex supply chains in the world; a portion of which supports aircraft MC. Specifically, ensuring on-time and cost effective stocking and delivery of parts in order to minimize customer wait time (CWT) is critical for achieving target aircraft MC rates. Considerable amounts of time, money and manpower are invested in this within the United States Air Force. As a function of TNMCS, MC rates are used to determine the Air Force's overall operational readiness. While much literature is available on total non-mission capable [due to] maintenance (TNMCM), little published work exists which explicitly investigates TNMCS rates for

AF weapon systems. With mixed results for each weapon system, one study done by Air Force Materiel Command (AFMC) analysts (Fryman et al, Aug 2008) found that spares funding level as a percent of the weapon system's requirement was overall not a good predictor of TNMCS. Another similar study was done to develop an explanatory model for TNMCS based on current supply performance data. While some positive outcomes were found on an individual weapon system level, no conclusive results related TNMCS to these specific performance metrics across all weapon systems. More specifically, and of key importance to this research, was that for the B-1, no significant factors were found that impacted TNMCS. As a novel approach to understanding TNMCS, simulation provides a method of stepping back such that further insight can be gained (Weir, 2009).

Influenced by various stochastic elements and external factors, the AF supply chain that supports aircraft maintenance for a single fleet of aircraft at an individual air base, as in our problem, is itself a complex system. Whether investigating the stocking policies at individual points in the supply chain, or simply the aggregated logistics response time, every node in the network is critical to providing a lean and agile supply chain. While much of the system is understood and strictly monitored at an individual level, little is understood about the behavior of the broad process. Thus, a simulated abstraction of the system is warranted so that estimates of the desired true characteristics may be discovered (Law, 2007). Simulation is an ideal method for studying complex systems, as well as exploring how changes to the inputs affect the responses (Banks, 2005).

3.3 AF Supply Chain Simulation

With the complexity of the AF supply chain understood, an abstraction is developed that models the system such that sufficiently accurate interpretations can be made. By applying this abstraction to a well defined situation, simulation provides a beneficial first look at how the system operates. The specific focus of this research is the investigation of the B-1 Code 3 landing requirements within the supply chain. Additionally, a single fleet of aircraft at Ellsworth, AFB is investigated.

3.3.1 Model Development

A discrete event simulation was developed using ARENA® software. For this study, several key assumptions underlie our model. These are:

- All reparable parts are sourced from ALC
- All consumable parts are sourced from the Defense Logistics Agency (DLA)
- Reparable parts only sourced laterally if not at ALC
- DLA process modeled purely as a delay
- No cannibalization (CANN), or sourcing of parts from currently NMC aircraft, is modeled
- No maintenance actions are explicitly modeled

- NMC [due to] Both [supply and maintenance] NMCB is inherent when calculating MICAP hours, thus resulting in sufficiently accurate estimates of TNMCS
- If a part is not MICAP it goes directly to base supply with no depot-level processing

Various echelons within the AF supply chain are available to support the unscheduled requirements for aircraft as they are broken. Figure 11 presents a generalized diagram of the various organizations which support B-1 MC through supply fulfillment.

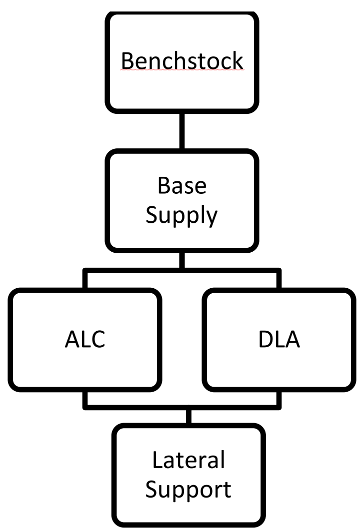


Figure 11. AF Supply Chain Echelon

Figure 12 shows the abstraction of the modeled supply chain process. Within the model, aircrafts enter the system as an entity based upon a time until next failure (TNF) distribution defined by Park (2010). The aircraft is then separated into individual broken parts which flow through the system as independent entities. Finally, when all parts for an individual aircraft are collected from the supply chain, the aircraft is in normal operations and re-enters the cycle as the entity. Sixteen aircraft are modeled at a single air base as the size of a representative fleet of aircraft at any given time when considering Programmed Depot Maintenance (PDM) and deployments.

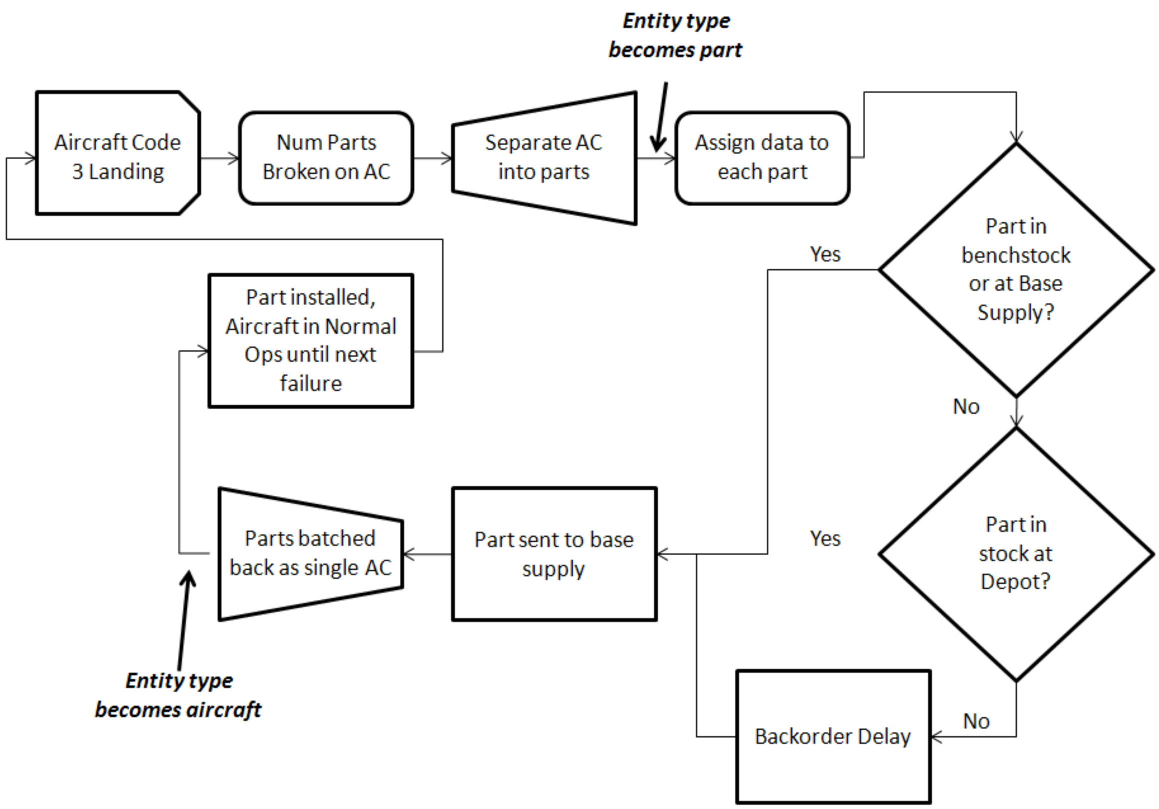


Figure 12. Modeled Supply Chain Process

The model is run for five years of simulated time per replication. Twenty replications were run so that a sufficiently accurate level of variation is found from the model. For each replication, an intelligent initialization period of 50 days is used to ensure aircraft are placed at various locations within the supply chain before collecting statistics.

3.3.2 Supporting Data, Verification and Validation

To drive various stochastic elements within the simulation, maintenance and supply data for a five year period (Jan 05-Dec 09) was gathered from the Logistics Installations and Mission Support – Enterprise View (LIMS-EV) as well as from maintenance and logistic subject matter experts (SMEs). The various distributions that were fit as inputs for the model are listed in Table 9. Additionally, from this data, individual part information was compiled and categorized by federal stock class (FSC) number, with thirty-two FSCs explicitly modeled (the remaining parts are represented by a single consolidated FSC). These FSCs were selected such that more than 80% of supply requisitions and MICAP hours were captured from the historical data.

Table 9. Fit distributions

Description	Expression
Number of Broken Parts	DISC(.53,1,.79,2,.89,3,.94,4,…,1,12)
ALC Backorder Delay	MX(1,ANINT(-.001 + LOGN(ALC_α,ALC_β))
DLA Processing Delay	MX(1,ANINT(-.001 + LOGN(DLA_α,DLA_β))
Lateral Processing Delay	MX(1,ANINT(-.001 + LOGN(Lat_α,Lat_β))
Time until Next Failure	MX(0,1.5*ANINT(-0.001+WEIB(TNF_ α,TNF_β)))

ANINT – Rounds the expression to the nearest integer
DISC – Expression pulls values from a discrete distribution with given parameters
LOGN – Expression pulls values from a Lognormal Distribution with given parameters
MX – Maximum Value of all values in the expression
WEIB – Expression pulls values from a Weibull Distribution with given parameters

As any simulation study requires, verification and validation were key elements in the development of our model. Ensuring the appropriate collection of MICAP and TNMCS hours was a significant means for verification, while various discussions with

SMEs and AFMC analysts assisted in our validation efforts. Additionally, certain outputs were analyzed against historic data to ensure that the simulation sufficiently captured the nature of the real system.

3.4 Initial Results and Analysis

The baseline system provides substantial insight into which factors have a significant impact on B-1 TNMCS rates. Upon completion of our model, an experimental design was performed to quantitatively investigate these factors. The first three factors modeled (ALC SE Rate, Base Supply SE Rate) represent how frequently parts are available at these two echelons in the supply chain. Lateral % gives an estimate for the percentage of parts sourced laterally, if the part is not able to be obtained via depot sourcing. Since the last four factors used unique distributions, a scaling factor was defined such that ±10% was used instead of attempting to change the shape and location parameters. Note for TNF, the base level was 1.5 times a fitted distribution. Table 10 shows the factors, and their associated levels used within the experimental design.

Table 10. Experimental design levels

Factor	Low level (-1)	Base level (0)	High level (+1)
ALC SE Rate	80%	85%	90%
Base Supply SE Rate	88%	90%	92%
Lateral %	4%	5%	6%
ALC B.O. Delay scaling factor (SF)	0.9*Expression	1.0* Expression	1.1*Expression
DLA Processing SF	0.9*Expression	1.0* Expression	1.1*Expression
Lateral Processing SF	0.9*Expression	1.0* Expression	1.1*Expression
TNF SF	1.35*Expression	1.5* Expression	1.65*Expression

When analyzing only the single factor effects, a quadratic pattern was discovered in the residuals, showing our error assumptions were violated and that higher order interactions needed to be modeled. At a 95% level of confidence, the results showed only two insignificant factors (Lateral % and Lateral Processing), as well as several significant two-factor interactions. Table 11 summarizes the significant factors for this model, while Figure 13 shows their interaction profile.

Table 11. Significant Factors

Factor	p-value	Factor	p-value
Intercept	<0.0001	**ALC SE*ALC SF**	0.0032
ALC SE	<0.0001	**ALC SE*Base SE**	<0,.0001
Base Supply SE Rate	<0.0001	**Base SE*DLA SF**	0.0057
ALC B.O. Delay	<0.0001	**ALC SF*TNF SF**	0.0244
DLA Processing	<0.0001	**Base SE*TNF SF**	<0.0001
TNF	<0.0001		

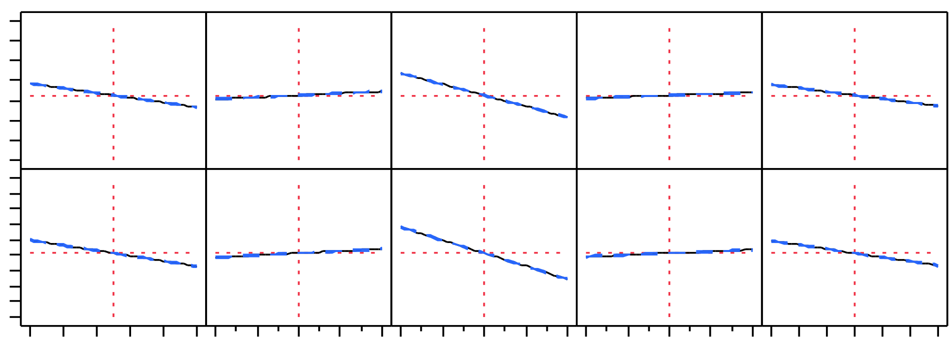


Figure 13. Significant Factors Prediction Profile

Figure 13 shows us that changes in SE appear to have a larger impact on TNMCS than changes in the individual delays. The associated metamodel derived from this experimental design was also found significant, explaining almost all of the data (R^2_{adj} = 0.9979).

3.5 Comparison of Two ALC Stockage Effectiveness Policies

The discovery of these significant factors is a beneficial first step in providing further insight into the true nature of the supply chain's effect on TNMCS rates. As an additional investigation, three ALC SE policies were modeled to provide increased fidelity for this area of the model. The baseline policy, as part of the initial simulation, was a constant rate of 85% for all parts. This rate is a sufficient representation of the SE levels for the ALCs that support B-1 supply requirements. However, discussions with a logistics specialist from Ellsworth AFB brought to light the issue of certain categories of parts (FSCs) having significantly worst depot-level SE (Milnes, 2010). The two additional policies were developed and inserted into the model to see how they would affect TNMCS rates, and to possibly provide a greater level of fidelity to our model. These scenarios are:

1. Each FSC uses an individual ALC SE distribution expression (shown in Table 12)
    - Distributions were generated for 5 FSCs (suggested by Ellsworth SME) based on SE at three supporting ALCs

- A distribution was generated using data from all ALCs and used as the SE policy for the remainder of the FSCs

Table 12. Source of Supply and Associated Distributions for Selected FSCs

	Ogden (FGZ)	Tinker (FHZ)	W-Robins (FLZ)	Distribution
1630 - AC Wheel and Brake Systems	X			UNIF(96,100)
5865 - Electric Countermeasures			X	TRIA(40,51.7,79)
1560 - Airframe Structural Components		X		TRIA(79,92.8,95)
5985 - Antennas, Waveguides		X	X	40 + 55*BETA(0.851, 0.528)
2835 - Gas Turbines, Jet Engine and Components	X			UNIF(96,100)
Remaining FSCs	X	X	X	40 + 60*BETA(0.888, 0.38)

2. The single distribution used to define the SE for the remainder of the FSCs in the first alternative policy was used
    - All FSCs assumed to fall under this distribution
    - Rates from all ALCs used to generate distribution

These distributions were inserted into the original model, with TNMCS maintained as the response. Figure 14 shows TNMCS as a response by replication for the three systems.

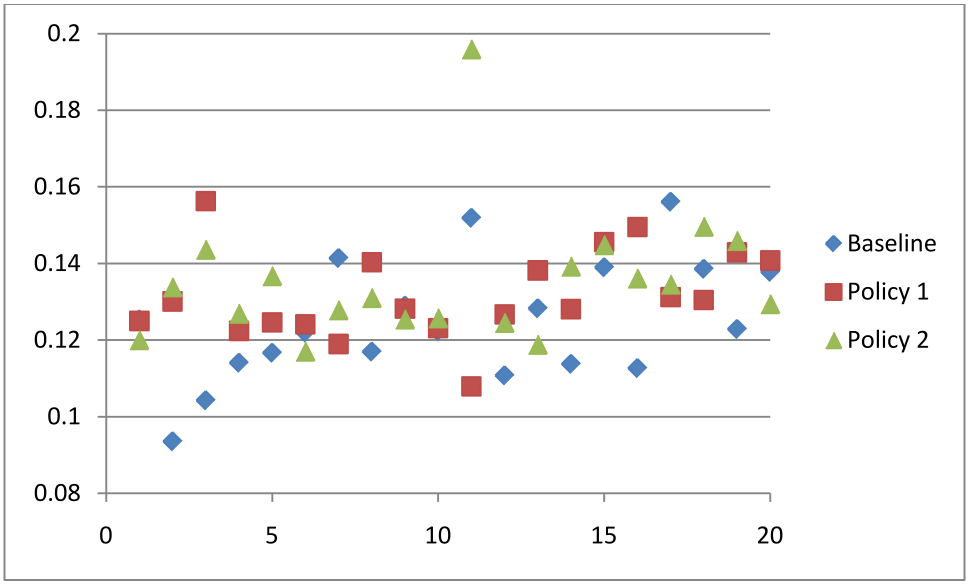


Figure 14. TNMCS Rate by Replication

Little direct information can be obtained from this chart, as there do not seem to be explicit differences within the three systems. In order to quantify these results, paired t-tests were run for each permutation of the three systems. The results are summarized in Table 13. For both scenarios 1 and 2, TNMCS increased at a significant level (approximately 1%) with the inclusion of these new distributions.

Table 13. Paired t-test resuls

	Result	Estimated Mean Difference
Base vs 1	Means Not Equal	-0.0093
Base vs 2	Means Not Equal	-0.0129
1 vs 2	Means Equal	-0.0036

This further investigation shows that variation even within the various ALCs can be a significant cause for an increase in TNMCS rates for a weapon system

3.6 Conclusions

This model and analysis examine the impact various factors can have on TNMCS rates for a single weapon system at a single air base. The intent of this study is not to provide optimum policies for various factors within the supply chain, but to gain further insight through the use of a generalized simulation model. Additionally, it is important to see how a slight increase in fidelity can further substantiate the responses. The results presented show several significant factors, as well as interactions among the factors. By further investigating these factors, a greater understanding of the TNMCS process can be obtained, and better policies can be implemented. Monitoring and adjusting these guidelines can directly impact AF MC rates.

4. Conclusion

4.1 Research Summary

This thesis develops a simulation as a novel approach to understanding factors which affect TNMCS rates for the B-1 bomber. The core processes within the supply chain were captured and historical data was used to drive the stochastic elements. This model represents an initial simulation framework which provides insight previously unavailable, while looking at factors not investigated in prior research.

Additional analysis examined the impact of variation of SE at the different ALC depots within the AF supply chain. While further investigation on the difference in impact of other factors was not performed, it is apparent that further issues exist even within three supporting depots. This type of fidelity is of crucial importance when modeling complex systems and provides further insight into the original simulation.

4.2 Future Work

The current base of published work investigating TNMCS is severely lacking. With MC being of key importance in representing the health of AF weapon systems, decreasing TNMCS to cost-effective rates is critical. This simulation provides some initial insight into what factors affect TNMCS, but as it represents a small fleet at a single air base, significant room for expansion is present.

An initial area for investigation would be to expand the number of aircraft, while looking at multiple air bases. The B-1 itself are housed at two main air bases (Ellsworth AFB, SD and Dyess AFB, TX), and as this research provides insight for a single air base, it is assumed that the factors could be substantially different when adding other locations. Additionally, the B-1 has deployment locations, so outside of 2 stationary air bases, the supply chain must be agile for wartime requirements as well.

Another key area for expansion is the inclusion of maintenance activities when modeling the TNMCS processes. While maintenance is generally tracked separately, there is likely some relation between these various actions and their requirements on the supply chain. The HVM study performed by Park (2010) provided a slight overlap between maintenance and TNMCS, but little fidelity was included in the modeled supply processes. Investigating how scheduled maintenance activities, such as PDM, impact the requirements on the supply chain would provide additional understanding.

Expanding the scope of this research to individual part types would be extensively time consuming, but if properly modeled, would add a level of fidelity that would likely pay dividends in the long run. Additionally, an investigation into some of the seemingly low-cost FSCs modeled within this research could produce interesting results if including costs within the simulation. Further expansion could come by increasing the fidelity of the modeled depot level processes. While little can be done to modify policies within the DLA, including additional processes within their organization could help when future requirements are negotiated. Similarly, as discussed in Chapter 3, by increasing the accuracy of the stochastic elements by introducing the various local sources, better estimates of the responses may be achieved.

Finally, as this model hopes to provide an initial structure for AF supply chain simulation, additional weapon systems should be modeled together, at several different air bases, both foreign and domestic. Alongside this type of augmentation should also be the inclusion of all of the depot locations, each responsible for their individual parts. Additionally, manpower, in the form of resources within a simulation framework, could be modeled to see how various manning levels affect TNMCS rates.

Appendix A. Arena Model Screenshots

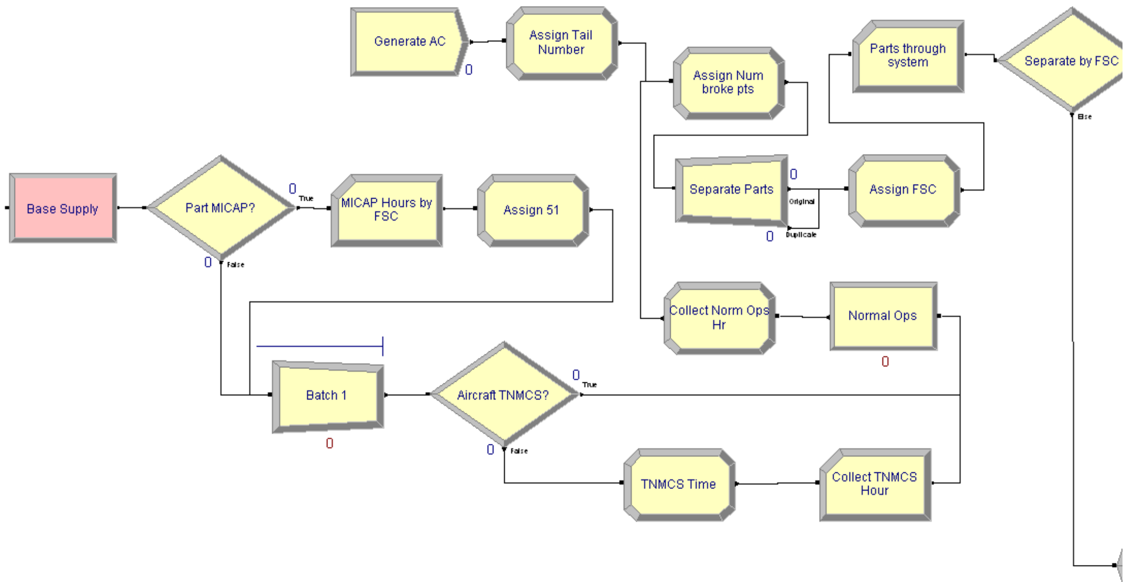


Figure 15. Main Model Logic

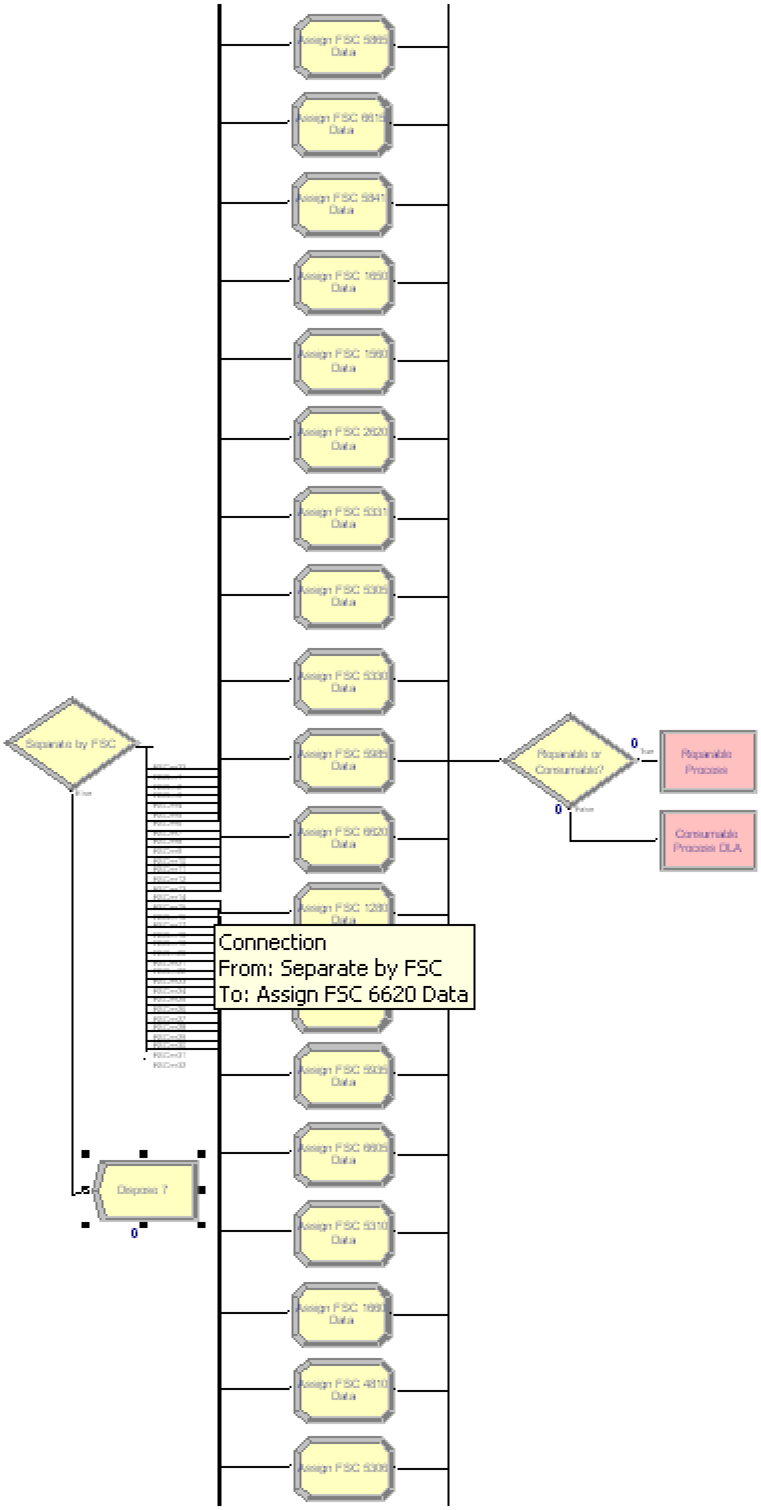


Figure 16. Branch by FSC and Reparable Consumable Transfer Logic

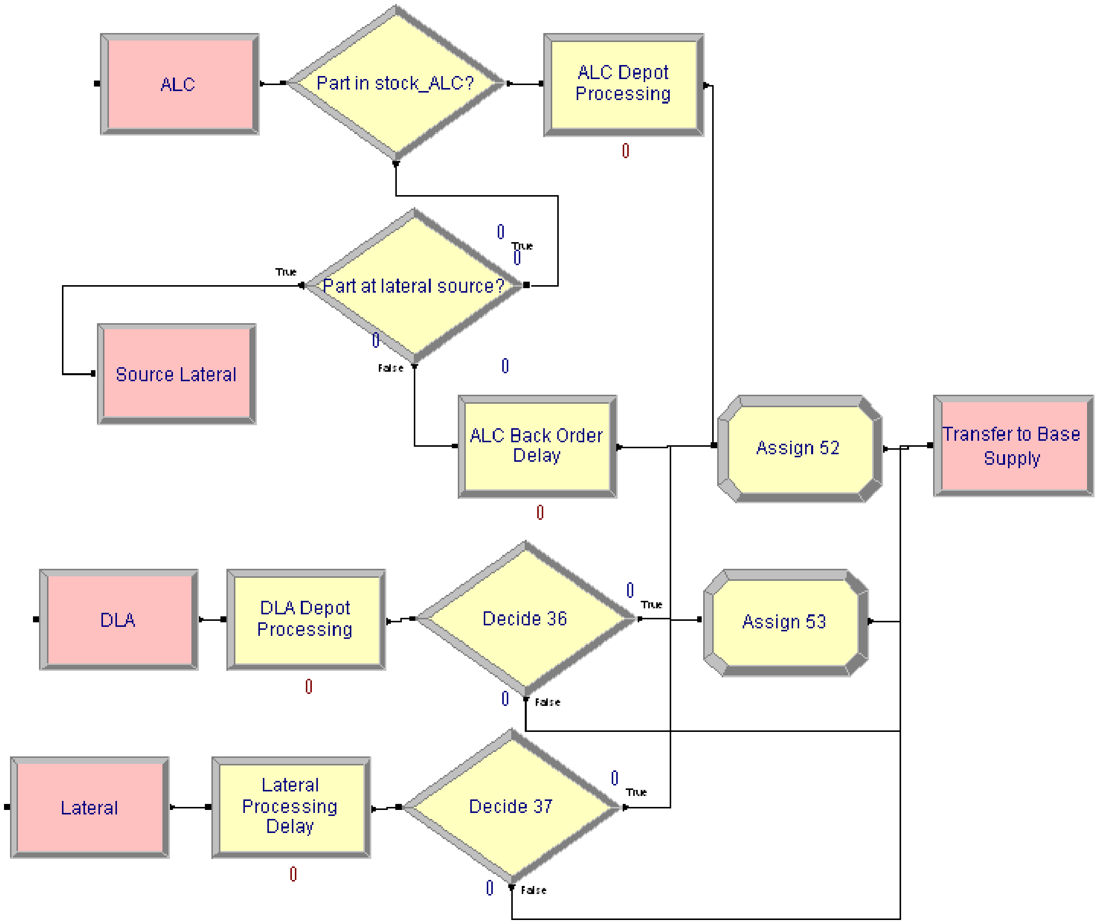
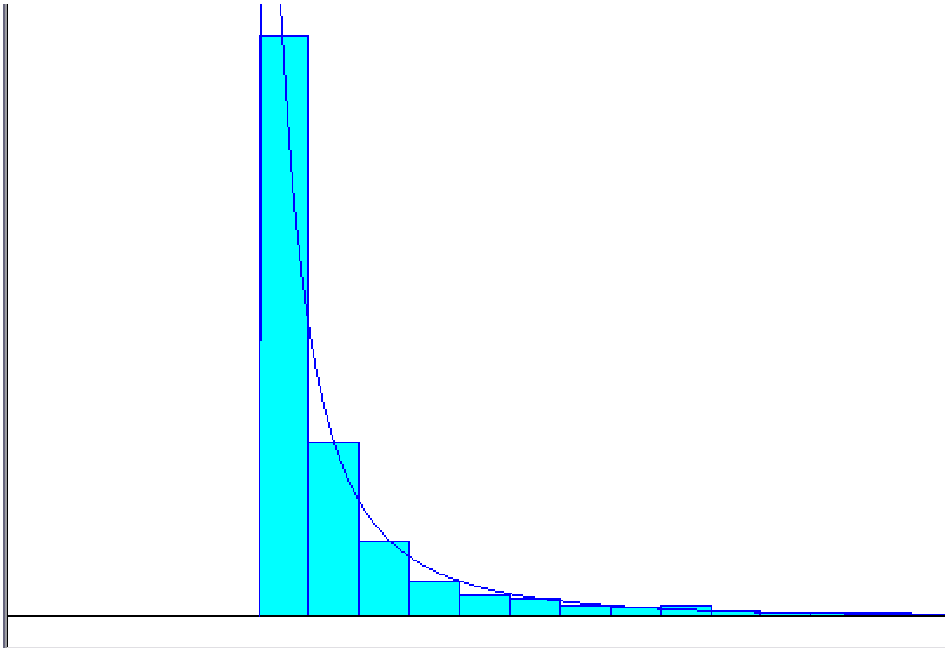


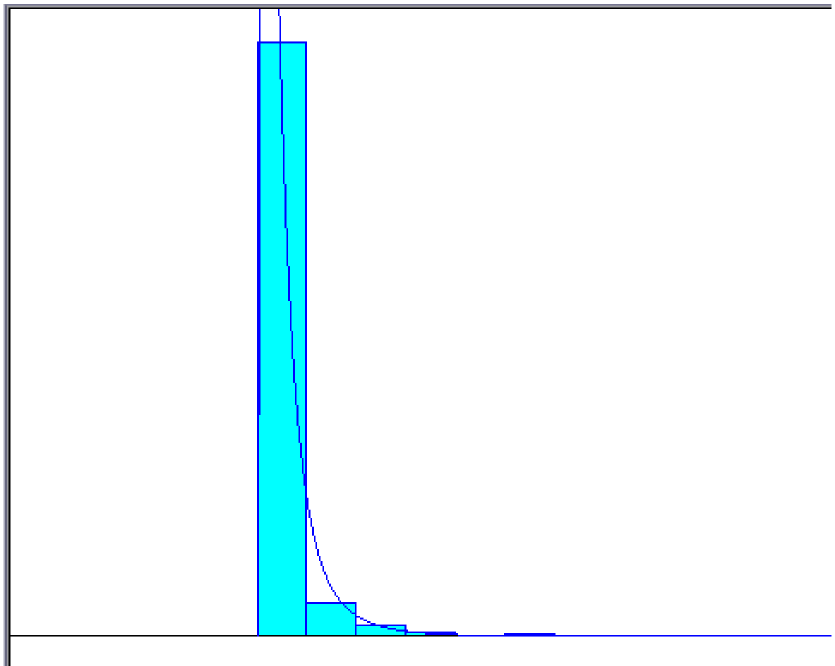
Figure 17. Source of Supply Logic

Appendix B. Input Distribution Reports



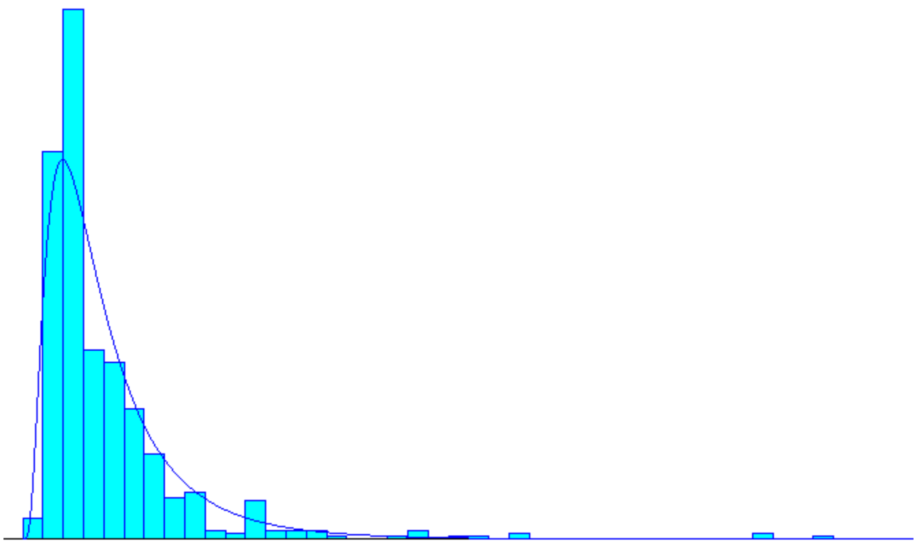
```
        Distribution Summary

Distribution:    Lognormal
Expression:      -0.001 + LOGN(24.1, 54.8)
Square Error:    0.001130

Chi Square Test
  Number of intervals    = 14
  Degrees of freedom     = 11
  Test Statistic         = 19.1
  Corresponding p-value  = 0.0611

Kolmogorov-Smirnov Test
  Test Statistic         = 0.0791
  Corresponding p-value  < 0.01

        Data Summary

Number of Data Points    = 1850
Min Data Value           = 0
Max Data Value           = 484
Sample Mean              = 23.2
Sample Std Dev           = 43.7

        Histogram Summary

Histogram Range          = -0.001 to 484
Number of Intervals      = 40
```

Figure 18. ALC Backorder Delay Distribution



```
        Distribution Summary

Distribution:   Lognormal
Expression:     -0.001 + LOGN(6.06, 7.06)
Square Error:   0.001468

Chi Square Test
  Number of intervals   = 5
  Degrees of freedom    = 2
  Test Statistic        = 273
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.139
  Corresponding p-value < 0.01

        Data Summary

Number of Data Points   = 4089
Min Data Value          = 0
Max Data Value          = 487
Sample Mean             = 7.02
Sample Std Dev          = 18.5

        Histogram Summary

Histogram Range         = -0.001 to 487
Number of Intervals     = 40
```

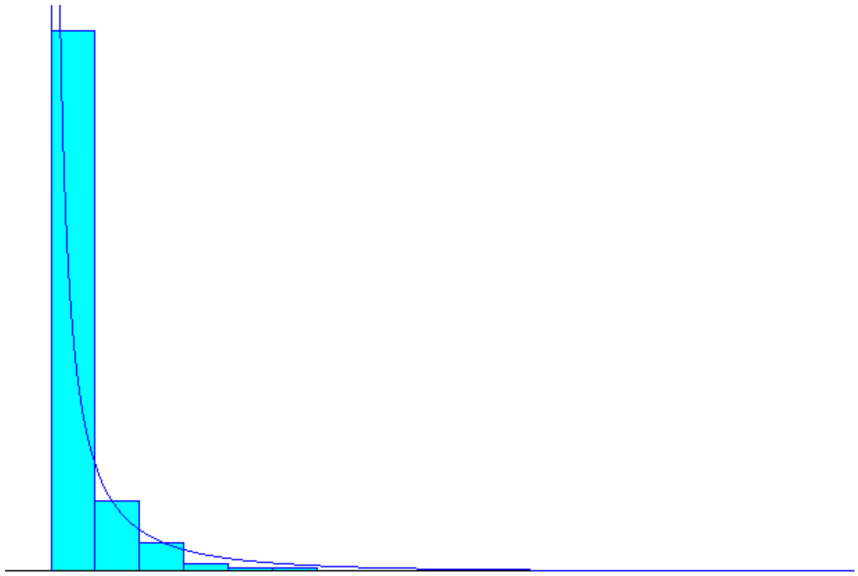
Figure 19. DLA CWT Delay Distribution



```
        Distribution Summary

Distribution:   Lognormal
Expression:     -0.5 + LOGN(4.26, 3.53)
Square Error:   0.015521

Chi Square Test
  Number of intervals   = 13
  Degrees of freedom    = 10
  Test Statistic        = 72.3
  Corresponding p-value < 0.005

        Data Summary

Number of Data Points   = 588
Min Data Value          = 0
Max Data Value          = 68
Sample Mean             = 4.12
Sample Std Dev          = 6.38

        Histogram Summary

Histogram Range         = -0.5 to 68.5
Number of Intervals     = 69
```

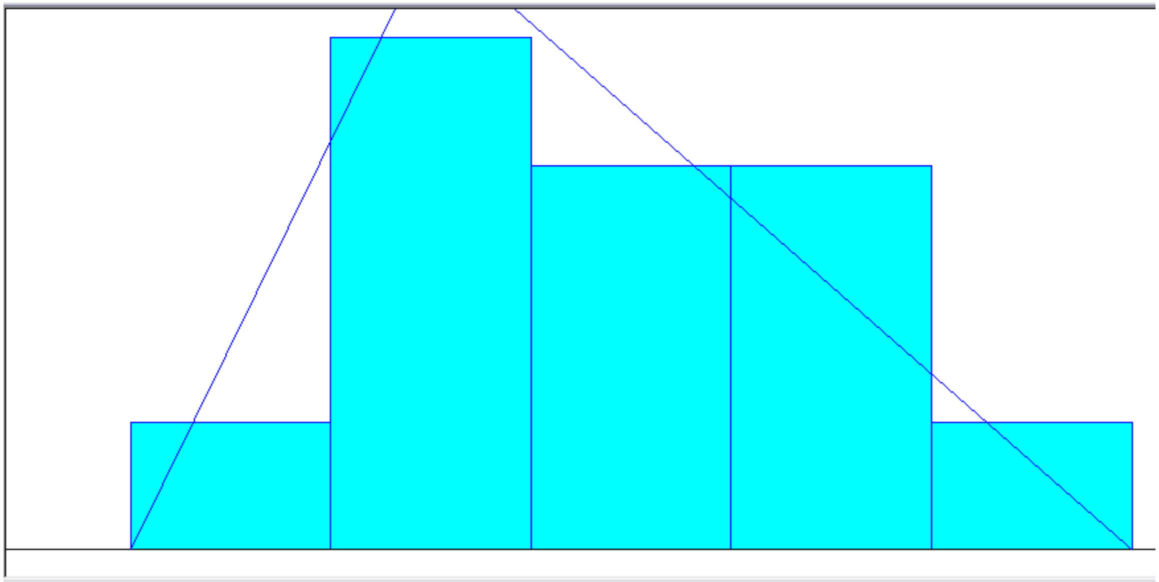
Figure 20. Lateral CWT Delay Distribution

Time to Next Failure distribution



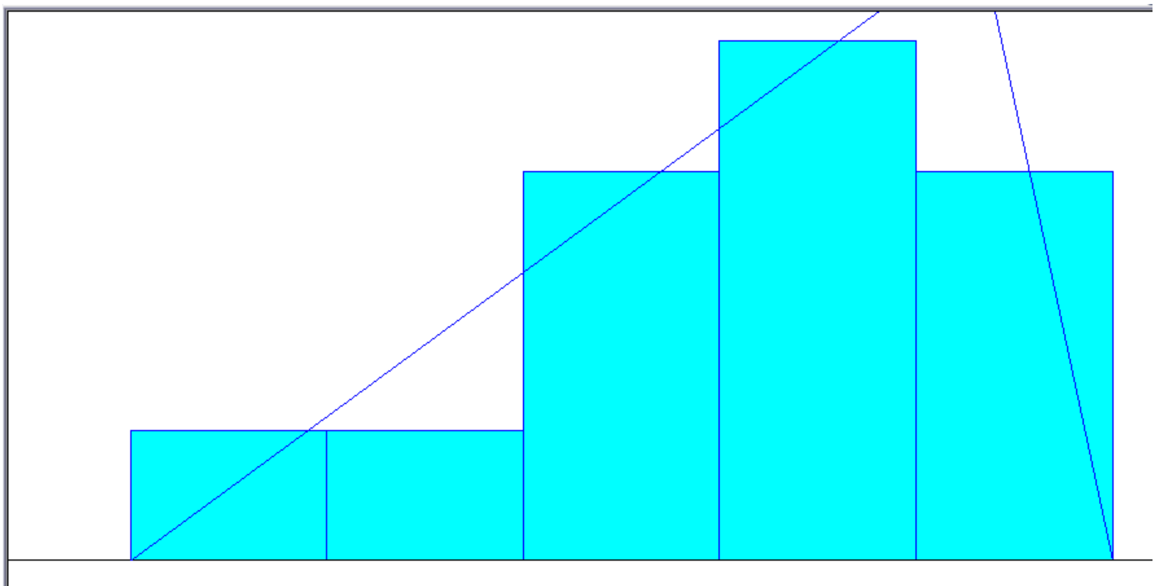
```
        Distribution Summary

Distribution:   Weibull
Expression:     -0.001 + WEIB(2.33, 0.47
Square Error:   0.002604

Chi Square Test
  Number of intervals   = 8
  Degrees of freedom    = 5
  Test Statistic        = 41.9
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.297
  Corresponding p-value < 0.01

        Data Summary

Number of Data Points   = 1032
Min Data Value          = 0
Max Data Value          = 171
Sample Mean             = 4.13
Sample Std Dev          = 10.7

        Histogram Summary

Histogram Range         = -0.001 to 171
Number of Intervals     = 32
```

Figure 21. Time to Next Failure (TNF) Distribution



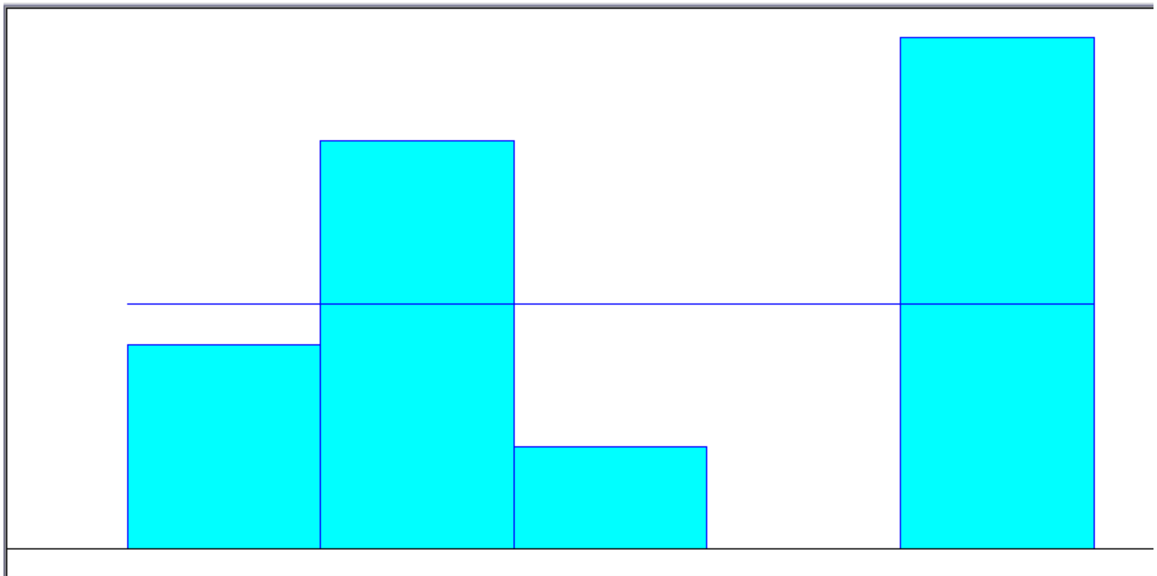
```
        Distribution Summary

Distribution:   Triangular
Expression:     TRIA(40, 51.7, 79)
Square Error:   0.010998


Kolmogorov-Smirnov Test
  Test Statistic        = 0.292
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 12
Min Data Value          = 40.5
Max Data Value          = 78.2
Sample Mean             = 58.9
Sample Std Dev          = 10.7

        Histogram Summary

Histogram Range         = 40 to 79
Number of Intervals     = 5
```

Figure 22. Warner Robins (FLZ) SE Distribution



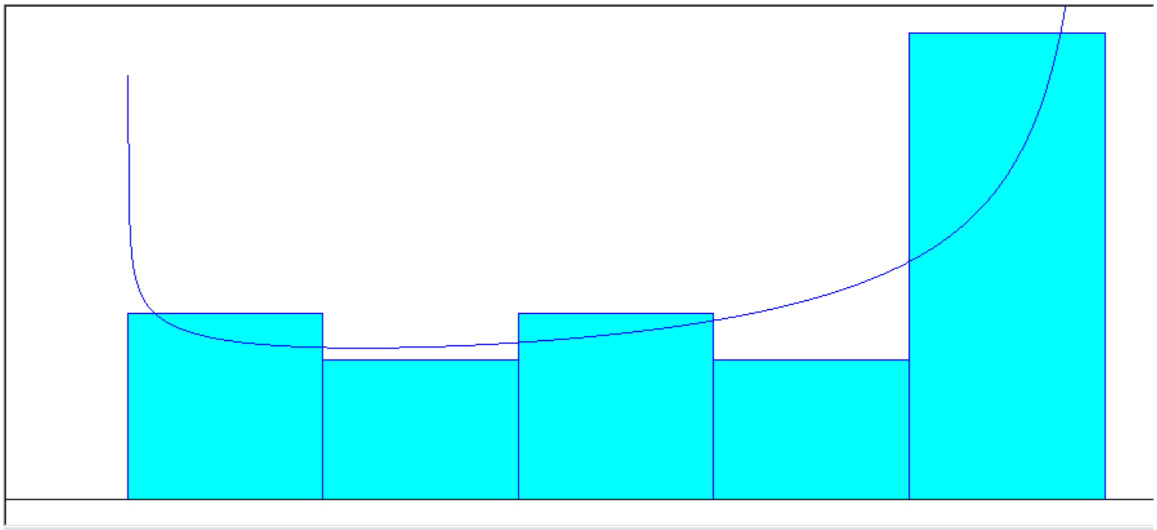
```
        Distribution Summary

Distribution:   Triangular
Expression:     TRIA(79, 92.8, 95)
Square Error:   0.004974


Kolmogorov-Smirnov Test
  Test Statistic        = 0.185
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 12
Min Data Value          = 79.7
Max Data Value          = 94.6
Sample Mean             = 88.9
Sample Std Dev          = 4.62

        Histogram Summary

Histogram Range         = 79 to 95
Number of Intervals     = 5
```

Figure 23. Tinker (FHZ) SE distribution



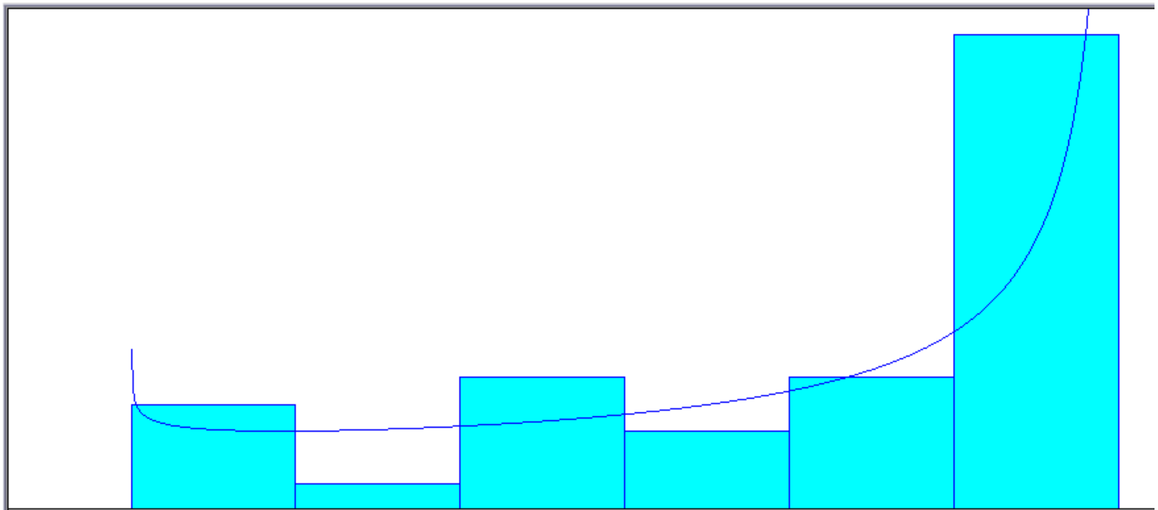
```
        Distribution Summary

Distribution:   Uniform
Expression:     UNIF(96, 100)
Square Error:   0.119444


Kolmogorov-Smirnov Test
  Test Statistic        = 0.416
  Corresponding p-value = 0.0224

        Data Summary

Number of Data Points   = 12
Min Data Value          = 96.3
Max Data Value          = 100
Sample Mean             = 98.2
Sample Std Dev          = 1.6

        Histogram Summary

Histogram Range         = 96 to 100
Number of Intervals     = 5
```

Figure 24. Ogden (FGZ) SE Distribution



```
        Distribution Summary

Distribution:   Beta
Expression:     40 + 55 * BETA(0.851, 0.528)
Square Error:   0.006706

Chi Square Test
  Number of intervals   = 3
  Degrees of freedom    = 0
  Test Statistic        = 0.257
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.0795
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 24
Min Data Value          = 40.5
Max Data Value          = 94.6
Sample Mean             = 73.9
Sample Std Dev          = 17.3

        Histogram Summary

Histogram Range         = 40 to 95
Number of Intervals     = 5
```

Figure 25. FHZ/FLZ joint SE distribution



```
        Distribution Summary

Distribution:   Beta
Expression:     40 + 60 * BETA(0.888, 0.38)
Square Error:   0.039615

Chi Square Test
  Number of intervals   = 4
  Degrees of freedom    = 1
  Test Statistic        = 2.06
  Corresponding p-value = 0.17

Kolmogorov-Smirnov Test
  Test Statistic        = 0.211
  Corresponding p-value = 0.074

        Data Summary

Number of Data Points   = 36
Min Data Value          = 40.5
Max Data Value          = 100
Sample Mean             = 82
Sample Std Dev          = 18.2

        Histogram Summary

Histogram Range         = 40 to 100
Number of Intervals     = 6
```

Figure 26. All ALC joint SE distribution

Appendix C. FSC Descriptions

Table 14. Modeled FSC Descriptions (These 32 FSCs cover over 80% of all B-1 MICAP hours)

FSC	Description
1680	Miscellaneous Aircraft Accessories and Components
6610	Flight Instruments
1630	Aircraft Wheel and Brake systems
5865	Elect Countermeasures, Counter Countermeasures and Quick Reaction Capability Equipment
6615	Auto Pilot Mechanisms and Airborne Gyro Components
5841	Radar Equipment, Airborne
1650	Aircraft Hydraulic, Vacuum and De-icing System Components
1560	Airframe Structural Components
2620	Tires and Tubes, Pneumatic, Aircraft
5331	O-Rings
5305	Screws
5330	Packing and Gasket Materials
5985	Antennas, Waveguides, Related Equipment
6620	Engine Instruments
1280	Aircraft Bombing Fire Control Components
5895	Miscellaneous Communication Equipment
5935	Connectors, Electrical
6605	Navigational Instruments
5310	Nuts and Washers
1660	Aircraft Air Conditioning, Heat and Pressurizing Equipment
4810	Valves, Powered
5306	Bolts
6220	Electric Vehicle Lights, Fixtures
6150	Miscellaneous Elect Power and Distribution Equipment
4730	Fittings and Specialties; Hose, Pipe and Tube
6680	Liquid, Gas Flow, Liquid level and Mechanisms Motion Measuring Instruments
2995	Miscellaneous Engine Accessories, Aircraft
6110	Electrical Control Equipment
2835	Gas Turbines, Jet Engine and Components, Except Aircraft
6685	Pressure, Temp. and Humidity Measurement and Control Instruments
2915	Engine Fuel Systems Components, Aircraft
3120	Bearings, Plain, Unmounted

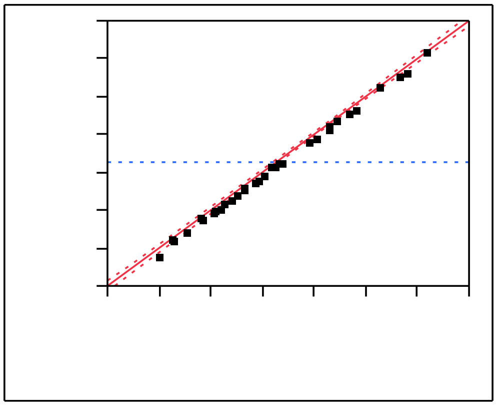
Appendix D. Experimental Design Matrix

Table 15. Full Factorial Design Matrix

	ALC_SE	ALC_SF	Base_SE	DLA_SF	TNF_SF	TNMCS Rate
+++++	90	1.1	92	1.1	1.65	0.091
++++−	90	1.1	92	1.1	1.35	0.108
+++−+	90	1.1	92	0.9	1.65	0.086
+++−−	90	1.1	92	0.9	1.35	0.103
++−++	90	1.1	88	1.1	1.65	0.127
++−+−	90	1.1	88	1.1	1.35	0.153
++−−+	90	1.1	88	0.9	1.65	0.118
++−−−	90	1.1	88	0.9	1.35	0.147
+−+++	90	0.9	92	1.1	1.65	0.087
+−++−	90	0.9	92	1.1	1.35	0.101
+−+−+	90	0.9	92	0.9	1.65	0.078
+−+−−	90	0.9	92	0.9	1.35	0.098
+−−++	90	0.9	88	1.1	1.65	0.121
+−−+−	90	0.9	88	1.1	1.35	0.145
+−−−+	90	0.9	88	0.9	1.65	0.114
+−−−−	90	0.9	88	0.9	1.35	0.138
0	85	1	90	1	1.5	0.12488
−++++	80	1.1	92	1.1	1.65	0.11
−+++−	80	1.1	92	1.1	1.35	0.127
−++−+	80	1.1	92	0.9	1.65	0.106
−++−−	80	1.1	92	0.9	1.35	0.125
−+−++	80	1.1	88	1.1	1.65	0.155
−+−+−	80	1.1	88	1.1	1.35	0.186
−+−−+	80	1.1	88	0.9	1.65	0.15
−+−−−	80	1.1	88	0.9	1.35	0.175
−−+++	80	0.9	92	1.1	1.65	0.102
−−++−	80	0.9	92	1.1	1.35	0.117
−−+−+	80	0.9	92	0.9	1.65	0.097
−−+−−	80	0.9	92	0.9	1.35	0.113
−−−++	80	0.9	88	1.1	1.65	0.15
−−−+−	80	0.9	88	1.1	1.35	0.173
−−−−+	80	0.9	88	0.9	1.65	0.14
−−−−−	80	0.9	88	0.9	1.35	0.167

Appendix E. Full Analysis Results (JMP)

Least Squares Fit
Response TNMCS Rate
Actual by Predicted Plot



Summary of Fit

RSquare	0.998557
RSquare Adj	0.997901
Root Mean Square Error	0.001286
Mean of Response	0.125239
Observations (or Sum Wgts)	33

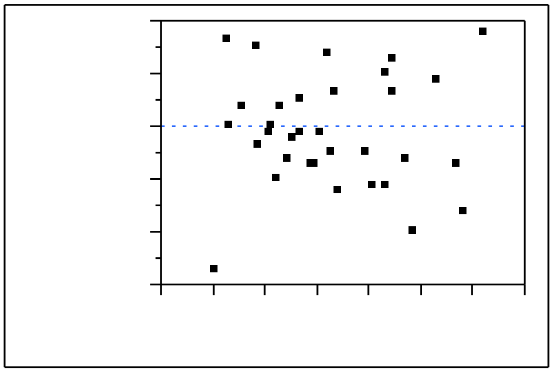
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	0.02517175	0.002517	1522.091
Error	22	0.00003638	1.654e-6	**Prob > F**
C. Total	32	0.02520813		<.0001*

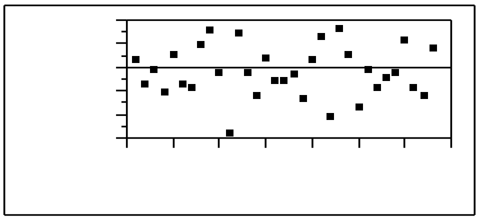
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.1252388	0.000224	559.45	<.0001*
ALC SE(80,90)	-0.011813	0.000227	-51.96	<.0001*
ALC SF(0.9,1.1)	0.0039375	0.000227	17.32	<.0001*
Base SE(88,92)	-0.022187	0.000227	-97.60	<.0001*
DLA SF(0.9,1.1)	0.0030625	0.000227	13.47	<.0001*
TNF SF(1.35,1.65)	-0.01075	0.000227	-47.29	<.0001*
ALC SE*ALC SF	-0.00075	0.000227	-3.30	0.0033*
ALC SE*Base SE	0.00275	0.000227	12.10	<.0001*
Base SE*DLA SF	-0.00075	0.000227	-3.30	0.0033*
ALC SF*TNF SF	-0.000562	0.000227	-2.47	0.0215*
Base SE*TNF SF	0.0023125	0.000227	10.17	<.0001*

Residual by Predicted Plot



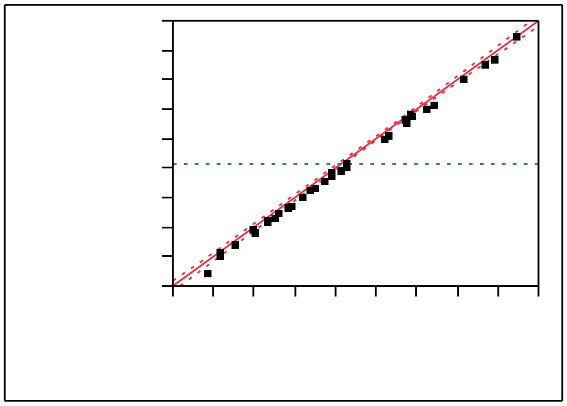
Residual by Row Plot



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	t Ratio	Prob>|t|
Base SE(88,92)	-0.022187	0.000227	-97.60		<.0001*
ALC SE(80,90)	-0.011813	0.000227	-51.96		<.0001*
TNF SF(1.35,1.65)	-0.01075	0.000227	-47.29		<.0001*
ALC SF(0.9,1.1)	0.0039375	0.000227	17.32		<.0001*
DLA SF(0.9,1.1)	0.0030625	0.000227	13.47		<.0001*
ALC SE*Base SE	0.00275	0.000227	12.10		<.0001*
Base SE*TNF SF	0.0023125	0.000227	10.17		<.0001*
ALC SE*ALC SF	-0.00075	0.000227	-3.30		0.0033*
Base SE*DLA SF	-0.00075	0.000227	-3.30		0.0033*
ALC SF*TNF SF	-0.000562	0.000227	-2.47		0.0215*

Response MICAP Hours
Actual by Predicted Plot



Summary of Fit

RSquare	0.998524
RSquare Adj	0.997853
Root Mean Square Error	969.249
Mean of Response	91313.1
Observations (or Sum Wgts)	33

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	1.3984e+10	1.3984e+9	1488.542
Error	22	20667761	939443.68	**Prob > F**
C. Total	32	1.4005e+10		<.0001*

Parameter Estimates

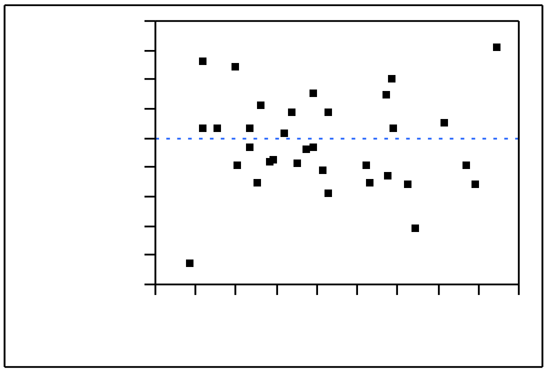
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	91313.099	168.7246	541.20	<.0001*
ALC SE(80,90)	-8441.856	171.3406	-49.27	<.0001*
ALC SF(0.9,1.1)	2702.3469	171.3406	15.77	<.0001*
Base SE(88,92)	-16835.07	171.3406	-98.25	<.0001*
DLA SF(0.9,1.1)	2176.5706	171.3406	12.70	<.0001*
TNF SF(1.35,1.65)	-7934.673	171.3406	-46.31	<.0001*
ALC SE*ALC SF	-566.0087	171.3406	-3.30	0.0032*
ALC SE*Base SE	1911.8456	171.3406	11.16	<.0001*
Base SE*DLA SF	-525.0594	171.3406	-3.06	0.0057*
ALC SF*TNF SF	-413.9806	171.3406	-2.42	0.0244*
Base SE*TNF SF	1701.2538	171.3406	9.93	<.0001*

Effect Tests

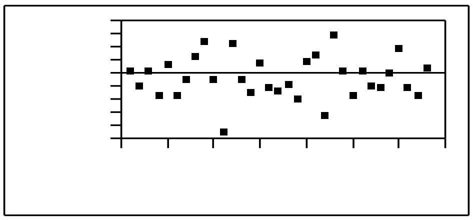
Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
ALC SE(80,90)	1	1	2280477645	2427.477	<.0001*
ALC SF(0.9,1.1)	1	1	233685716	248.7490	<.0001*
Base SE(88,92)	1	1	9069422581	9654.035	<.0001*
DLA SF(0.9,1.1)	1	1	151598710	161.3707	<.0001*
TNF SF(1.35,1.65)	1	1	2014688886	2144.555	<.0001*
ALC SE*ALC SF	1	1	10251709	10.9125	0.0032*
ALC SE*Base SE	1	1	116964918	124.5044	<.0001*
Base SE*DLA SF	1	1	8821995.11	9.3907	0.0057*
ALC SF*TNF SF	1	1	5484158.65	5.8377	0.0244*

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Base SE*TNF SF	1	1	92616458.3	98.5865	<.0001*

Residual by Predicted Plot



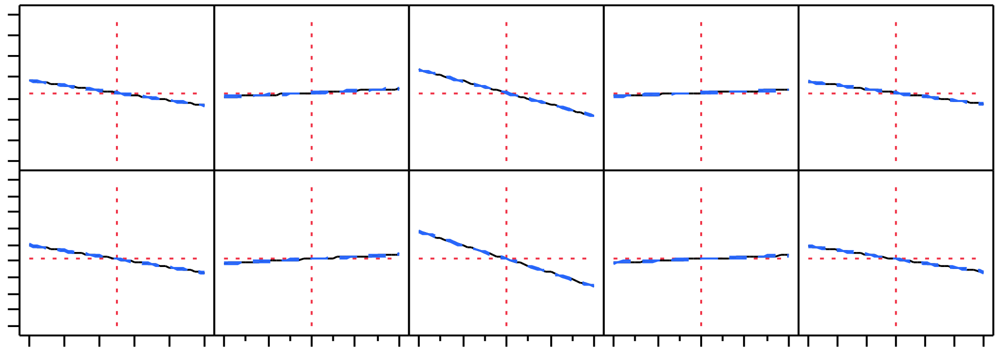
Residual by Row Plot



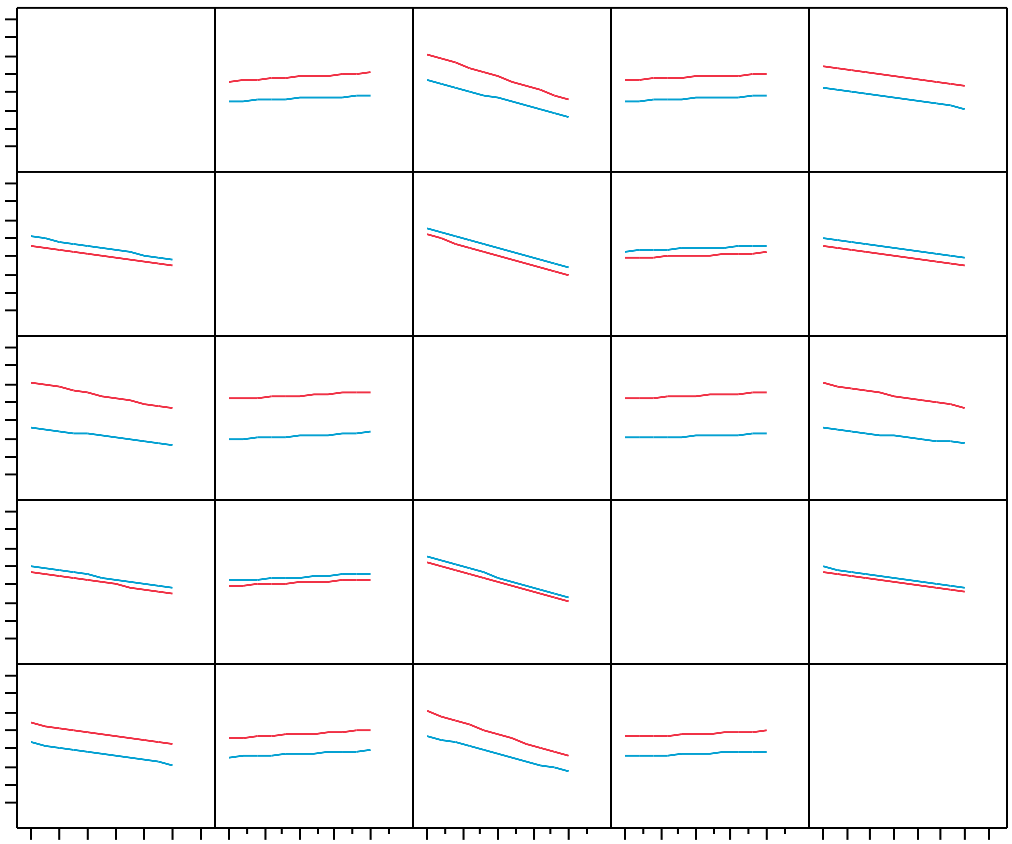
Sorted Parameter Estimates

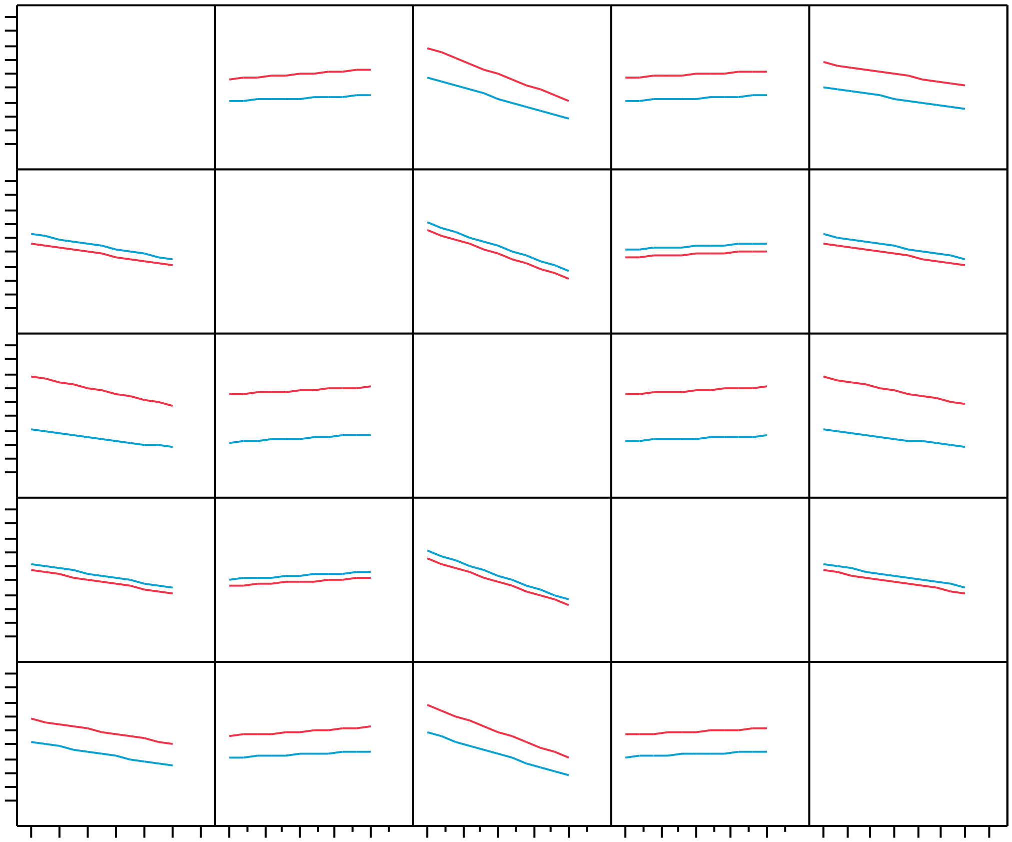
Term	Estimate	Std Error	t Ratio	t Ratio	Prob>|t|
Base SE(88,92)	-16835.07	171.3406	-98.25		<.0001*
ALC SE(80,90)	-8441.856	171.3406	-49.27		<.0001*
TNF SF(1.35,1.65)	-7934.673	171.3406	-46.31		<.0001*
ALC SF(0.9,1.1)	2702.3469	171.3406	15.77		<.0001*
DLA SF(0.9,1.1)	2176.5706	171.3406	12.70		<.0001*
ALC SE*Base SE	1911.8456	171.3406	11.16		<.0001*
Base SE*TNF SF	1701.2538	171.3406	9.93		<.0001*
ALC SE*ALC SF	-566.0087	171.3406	-3.30		0.0032*
Base SE*DLA SF	-525.0594	171.3406	-3.06		0.0057*
ALC SF*TNF SF	-413.9806	171.3406	-2.42		0.0244*

Prediction Profiler

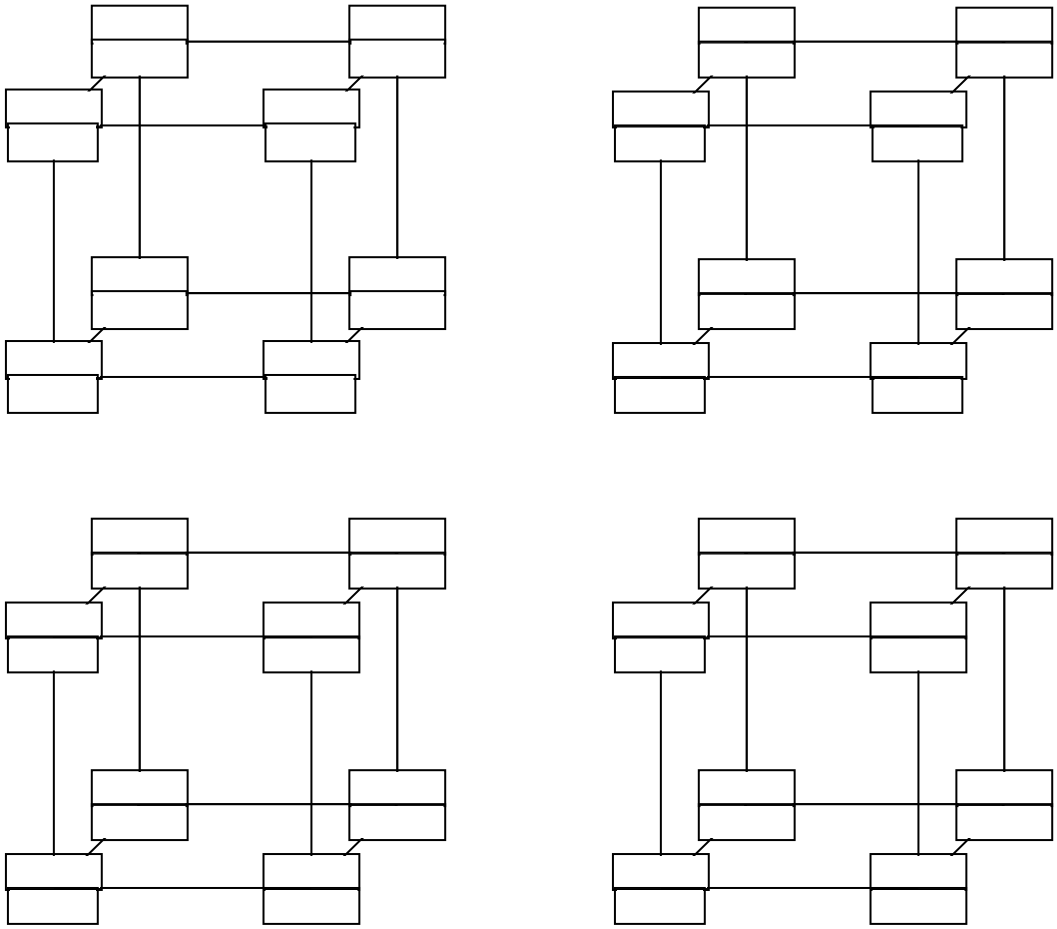


Interaction Profiles





Cube Plot*



*For each corner in the cube plots, the responses are represented as $\frac{TNMCS\ Rate}{MICAP\ Hours}$

Appendix F. Blue Dart

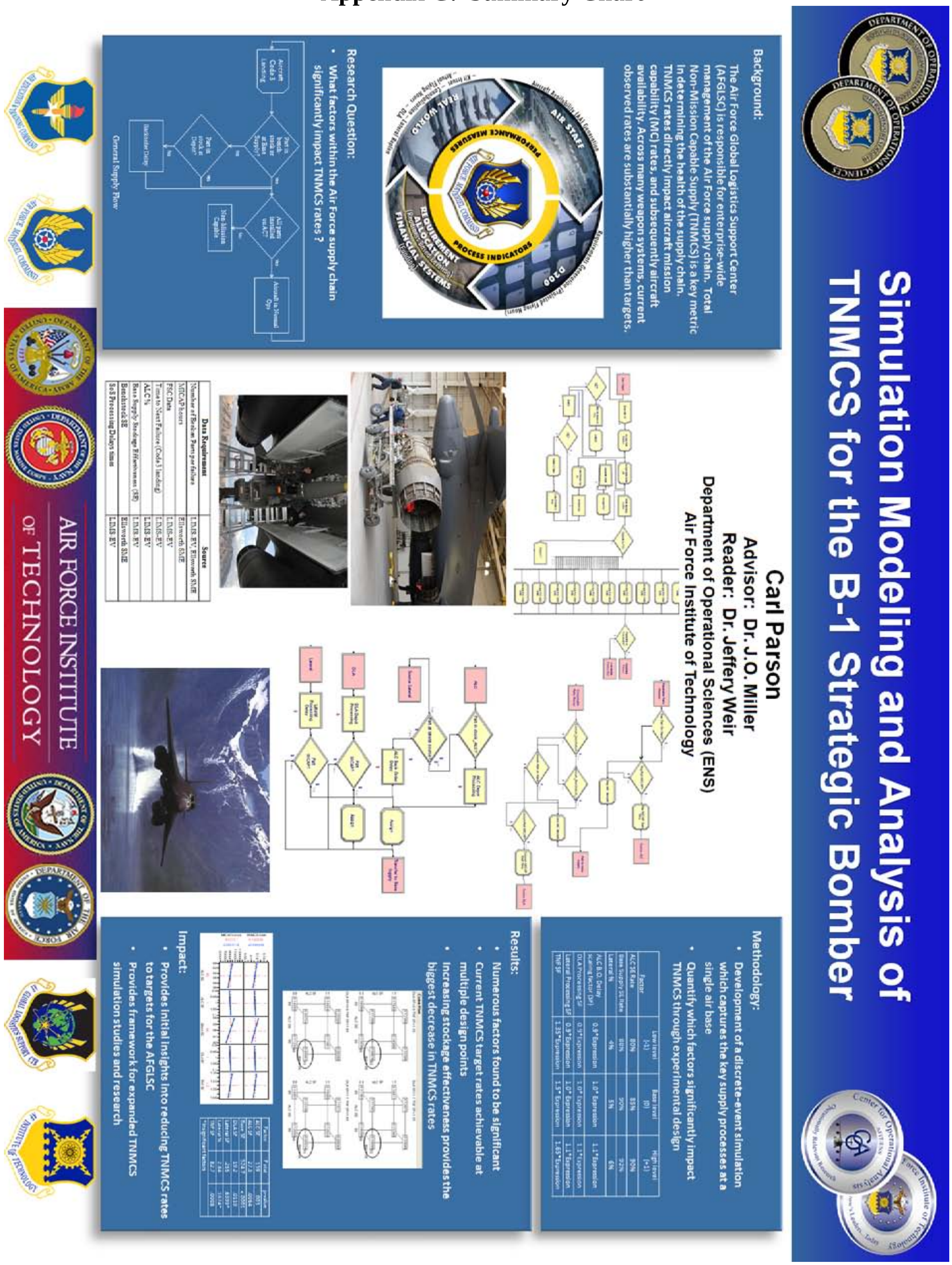
How to Keep More Aircraft Ready to Fly

Current AF supply chain metrics have significant meaning to the overall health of a fleet of aircraft. Air Force leadership relies on these management level metrics to set flying hour requirements, budget forecasts and readiness levels which all drive aircraft availability (AA). Underlying mission capability (MC) rates, a principal driver of AA, is Total Non-Mission Capable [due to] Supply (TNMCS), a key performance metric of the AF supply chain.

For many weapon systems, current achieved TNMCS rates are well above their target, which creates a cause for concern for key AF decision makers. As an ever present need exists to increase capability while reducing the economic impact of our policy decisions, further comprehension of what drives these metrics is required. Currently, little is quantitatively understood about what areas of the supply chain have significant impact on TNMCS rates, and therefore are the best areas to focus attention on for improvements.

To help identify supply chain players and activities that influence TNMCS rates, we developed a high-level simulation model of the supply chain processes for a single weapon system (the B-1 Strategic Bomber) at a single air base (Ellsworth AFB, SD). Our model tracked failed parts at the Federal Stock Class (FSC) level and their movement through the supply chain based upon probability distributions built using detailed historical data. Analysis of model results revealed a number of factors and how these factors affect TNMCS rates. These factors include base supply and depot stockage effectiveness, sourcing delays from the various suppliers, and time between aircraft failures. It was also interesting to note that some lower cost consumable items were significant contributors to increased TNMCS hours for individual aircraft. With promising results from our study at this level of detail, additional work can expand this approach to multiple weapon systems and air bases, providing a clearer picture of players and activities in the AF supply chain, where we can focus improvement efforts to keep more aircraft ready to fly.

Appendix G. Summary Chart



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14. ABSTRACT
Simulation provides a method of modeling complex systems which would otherwise be impractical for quantitative experimentation. While other analytic techniques have been used to explore Total Non-Mission Capable [due to] Supply (TNMCS) rates, simulation offers a novel approach to discovering what aspects of the supply chain impact this metric.

This research develops a discrete event simulation to investigate factors which affect TNMCS rates for the B-1B by modeling the core processes within the Air Force (AF) supply chain. A notional fleet of 16 aircraft at a single air base (Ellsworth AFB, SD) is modeled based on historical supply and maintenance data. To identify and quantify the effects of various factors, an experimental design is used for analyzing the output of our high-level discrete event simulation. Additionally, two different approaches to reporting and modeling Air Logistics Center (ALC) stockage effectiveness (SE) are compared to our baseline simulation. This exploration shows several factors which significantly impact TNMCS rates and have the potential to reduce them to their current targets.

15. SUBJECT TERMS
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